El Colegio de la Frontera Sur

Caracterización de los tipos de sistemas agroforestales de café mediante percepción remota

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Las personas abajo firmantes, integrantes del jurado examinador de:

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Dedicatoria

Le dedico el resultado de este arduo trabajo, primeramente, al Gran Creador del Universo, las bendiciones y aprendizajes me hicieron llegar hasta este momento. A mi familia por todo el apoyo en los buenos y malos momentos. Me han enseñado a ser la persona que soy hoy, mis principios, mis valores, mi perseverancia y mi fuerza. También a mis amigos, que de una u otra forma también me motivaron y ayudaron en este proceso.

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TABLA DE CONTENIDO

Resumen

Chiapas es el mayor productor de café a nivel nacional. Se estima que en esta entidad alrededor de 242,000 hectáreas están dedicadas a la producción del grano. A pesar de su importancia económica, cultural y ecológica, se desconocen aún algunas de las características de este sistema de producción, tales como la distribución espacial de las parcelas y los tipos de sistemas agroforestales (SAF) que lo conforman. El mapeo de las áreas de producción presenta grandes desafíos debido a que en su mayoría el café se produce en parcelas pequeñas, cultivadas bajo un SAF, dispersas a lo largo de regiones montañosas con difícil acceso. El objetivo de este trabajo fue desarrollar un enfoque metodológico basado en datos de observación de la Tierra para caracterizar los diferentes tipos de SAF de café en la Sierra Madre de Chiapas. Se emplearon imágenes mensuales ópticas (sentinel-2) y de radar (sentinel-1) de los primeros seis meses del año, un modelo de elevación digital, mapas de humedad del suelo y datos de campo obtenidos en 150 parcelas. Se calcularon índices de vegetación y se analizó la respuesta espectral de los cultivos a lo largo de la temporada de secas para identificar las temporadas más adecuados para discriminar los tipos de SAF. Con las imágenes satelitales y los datos complementarios se desarrollaron modelos para cada uno de los tipos de SAF identificados en campo. El modelo de clasificación empleó un algoritmo Random Forest de clasificación, las variables predictoras en cada uno de ellos se seleccionaron mediante un método denominado eliminación recursiva. Finalmente, los modelos ajustados se combinaron en uno solo para la construcción del mapa de los tipos de SAF. Para validar el modelo espacial se utilizó un conjunto de 932 sitios extraídos de imágenes Planet (resolución espacial de 4.5 m). De acuerdo con los patrones de respuesta espectral se identificaron tres tipos de SAF con diferentes características de densidad y composición de los árboles de sombra. Los sistemas agroforestales se ubicaron principalmente en áreas de bosque degradado y vegetación secundaria, donde principalmente se hace manejo de la vegetación natural para incorporación de las plantas de café en el sotobosque y algunas especies de árboles maderables y frutales para autoconsumo, en el caso de los policultivos. Se encontró una mayor extensión de sistemas rústicos, distribuidos principalmente en zonas colindantes con bosques maduros. Se obtuvo una precisión temática global de 95%, el tipo de SAF con mayor densidad arbórea obtuvo el mayor error de clasificación. Con respecto a los datos satelitales, la información en el rango infrarrojo (NIR) e infrarrojo cercano (SWIR) es particularmente útil, aunque es necesario el uso ¿el uso? de datos complementarios para reducir la incertidumbre. A pesar de que las imágenes de radar aportaron información para discriminar algunos SAF, ninguna de ellas fue seleccionada para permanecer dentro del modelo final. Además, nuestros hallazgos resaltan la efectividad del uso de diferentes conjuntos de datos bajo un enfoque multitemporal para la identificación de sistemas agrícolas complejos en áreas de alta heterogeneidad topográfica.

Palabras clave: Sierra Madre; Chiapas; Random Forest; café de sombra; Recursive Feature Elimination

Introducción

Los sistemas agroforestales (SAF) forman parte fundamental de las estrategias de conservación y manejo integrado del territorio (Farfán-Valencia 2019). A través de la diversificación y mantenimiento de la producción agrícola se busca aumentar la productividad, conservar la biodiversidad y disminuir los procesos de degradación de ecosistemas y erosión del suelo (Borelli et al. 2017). El éxito de estos sistemas se debe principalmente a la adaptabilidad a diferentes contextos socioeconómicos y ambientales y la flexibilidad en las técnicas de manejo de sus componentes (Muschler 2016; Jose 2019). Pese a que los SAF se han implementado a escala global, las prácticas agroforestales destacan en las regiones tropicales del planeta, donde los ecosistemas tropicales y templados ofrecen condiciones adecuadas para la producción agrícola bajo este esquema (Villavicencio-Enríquez 2013; Montagnini et al. 2015).

Uno de los principales cultivos bajo sistemas agroforestales de zonas tropicales es el café (*Coffea arabica L.*), ya que las capacidades fotosintéticas de las plantas de café están adaptadas a entornos bajo sombra (Zapata Arango 2019). A escala global, de la producción y comercialización del café dependen más de 20 millones de cafeticultores, principalmente de países en vía de desarrollo (Figueroa-Hernández et al. 2019).

En México, existe una amplia variedad de tipos de sistemas agroforestales de café debido a modificaciones en la densidad y composición del dosel sobre el café y cambios en las variedades y distribución de las plantas de café. Esta diversidad de técnicas de manejo es consecuencia de la incidencia de plagas y enfermedades, procesos de degradación de bosques, condiciones climáticas y de acuerdo al contexto socioeconómico de los productores (Montagnini et al. 2015; Valencia et al. 2018). En Chiapas, el estado con mayor producción de café (41% del total nacional) (INCAFECH 2019), se tiene la mayor superficie cultivada, distribuida en 198,320 predios con prácticas agroforestales y café a cielo abierto, con una superficie total de alrededor de 242,000 hectáreas (Flores Vichi 2015). En su mayoría, son áreas boscosas, con alta heterogeneidad topográfica y, generalmente, en sistemas agroforestales con estructuras de dos y tres estratos de vegetación (INCAFECH 2019).

En el estudio de SAF a diferentes escalas espaciales y temporales, la percepción remota constituye una herramienta fundamental. Sin embargo, la precisión del mapeo de las zonas agrícolas depende en gran medida de las características del área de cultivo y de los sistemas de producción, siendo los cultivos que se desarrollan bajo sombra forestal, los que presentan mayor error en su clasificación (Farfán-Valencia 2019).

En el proceso de construcción de imágenes satelitales ópticas, las condiciones climáticas, la heterogeneidad topográfica y la cobertura del dosel de los bosques limitan el alcance de la señal de los sensores ópticos y aumenta los efectos de dispersión, por lo que las imágenes contienen poca o nula información espectral útil para el estudio de estos sistemas (Baghdadi and Mehrez 2016); y a menudo sus patrones espectrales son confundidos con otros tipos de cobertura terrestre, como bosques o vegetación secundaria (Souza et al. 2016; Hunt, et al. 2020). Por otro lado, el haz de longitud de onda de microondas utilizado en la tecnología radar es capaz de penetrar el dosel. Sin embargo, la topografía en regiones montañosas genera efectos geométricos y radiométricos sobre la respuesta que reciben los sensores, como el escorzo o la inversión de la geometría (Richards 2009).

Uno de los enfoques más relevantes para abordar esta problemática, es el análisis en conjunto de datos que proveen información directa (imágenes ópticas, imágenes de radar y fotografías aéreas) y aquellos que proveen información indirecta (patrones de precipitación, humedad, clima, elevación, etc.). Sin embargo, estos análisis requieren de conocimiento amplio de las áreas de estudio y datos provenientes de visitas de campo que se utilicen como referencia.

Otro enfoque es el uso de técnicas y herramientas computacionales robustas para análisis de datos geoespaciales; por ejemplo, algoritmos de clasificación difusa a través de inferencias sobre pixeles sin información o con poca información mediante la construcción de reglas lógicas de clasificación (D’Negri and De Vito 2006; Ruvalcaba Coyaso and Vermonden 2016) o mezclas espectrales, ya sea a nivel de pixel individual o de un objeto con la información espacial, generalmente conocida como "espacio-contextual", indicando la relación entre un píxel "objetivo" y sus píxeles vecinos (Tso and Mather 1999), así como segmentación de imágenes, el análisis de imágenes basado en objetos (Blaschke 2010; Moser et al. 2013) y el uso de información adicional generada través de extracción de texturas, cálculo de índices de vegetación, entre otros.

En el caso de la cafeticultura en Chiapas, existe una carencia de información con respecto a la contribución de los diferentes tipos de SAF y a la distribución espacial de los mismos, principalmente debido a que una cantidad significativa de parcelas con producción de café se ubican en zonas de alta marginación dispersas en ecosistemas de montaña de difícil acceso (Higuera-Ciapara and Rivera-Ramírez 2018), además el 90% del café cultivado en el estado es bajo prácticas agroforestales. Las condiciones climáticas y topográficas dificultan el levantamiento de datos sobre la dinámica socioambiental en las áreas de producción de café, principalmente en áreas forestales de montaña. Además, el análisis de los SAF a través de percepción remota ha sido poco abordado y los resultados han tenido una alta incertidumbre.

El objetivo del presente trabajo de investigación es la caracterización de sistemas agroforestales de café con diferentes densidades de árboles de sombra en una de las regiones de mayor producción ubicada en la Sierra Madre de Chiapas, a través del análisis de las variaciones en la respuesta espectral temporal de los SAF y el uso de datos auxiliares.

En el capítulo siguiente se presenta una revisión del estado del arte del mapeo de áreas de producción de café y los estudios realizados para identificar sistemas agroforestales de café a nivel global a través de teledetección. Posteriormente se presenta la justificación del trabajo de investigación y su importancia para el monitoreo de las áreas de producción en Chiapas, así como los objetivos planteados.

En los capítulos siguientes se incorpora una sistemática de métodos computacionales de mapeo de sistemas agroforestales a lo largo de 20 años a escala global. En este trabajo se implementaron pruebas Kruskall-Wallis para comparar los métodos de clasificación de áreas con SAF de café a través de la precisión reportada en cada caso de estudio. Posteriormente, se incluye un trabajo publicado donde se realiza la caracterización de sistemas agroforestales mediante la implementación de algoritmos de *machine learning* y la combinación de información geoespacial en diferentes rangos del espectro electromagnético y datos auxiliares. Para ello, se definieron 3 clases de SAF de café y se construyeron conjuntos de datos geoespaciales diferenciados para la identificación de cada una de las clases definidas. A continuación, se presenta una discusión sobre los hallazgos más importantes en los análisis realizados para la caracterización de SAF de café en ambos trabajos. Los resultados mostraron una mayor dificultad para sistemas agroforestales con un mayor porcentaje de sombra y menor tecnificación del cultivo de café. Además, se identificó que el uso combinado de los rangos rojo (R), verde (G), azul (B) e infrarrojos permiten una mejor diferenciación de los sistemas agroforestales con cobertura forestal abundante. Finalmente, se incorporan reflexiones sobre el trabajo de investigación y posibles enfoques en trabajos futuros en un capítulo de discusión y uno de conclusiones.

Estado del arte

El café es un producto crucial para muchos países para el desarrollo económico y entender el proceso de cultivo y monitoreo puede tener implicaciones importantes tanto ambientales como económicas. En el mapeo del café, el uso de datos de percepción remota ha sido clave.

La percepción remota ha servido para diferentes fines en relación con el estudio del café. Por ejemplo, para monitorear la salud y el estado de las plantas de café, mediante el uso de imágenes espectrales e hiperespectrales. Los estudios han utilizado técnicas como NDVI (Índice de vegetación de diferencia normalizada) y EVI (Índice de vegetación mejorado) para evaluar la salud de la vegetación. Navarrete et al. (2017) utilizaron imágenes Landsat para evaluar las plantaciones de café en Colombia, centrándose en los cambios en el uso de la tierra y la cubierta vegetal. Su uso se extiende al impacto del cambio climático en la producción de café a través de factores como los patrones de temperatura y precipitación afectan las regiones cafetaleras. Baca et al. (2014) investigaron la vulnerabilidad de la producción de café al cambio climático en Centroamérica utilizando modelos climáticos y datos de teledetección.

En el estudio de sistemas agroforestales de café a través de percepción remota, las principales limitantes en la adquisición de datos se relacionan a la complejidad del paisaje, las variaciones en la cobertura arbórea y a la nubosidad y las condiciones climáticas que influyen en la cantidad y calidad de información contenida en imágenes aéreas o satelitales (Rizvi et al. 2013; Hunt, et al. 2020).

Pese a la gran variedad de métodos de clasificación, a escala global, el mapeo de sistemas agroforestales de café no ha sido claramente exitoso (Boell et al. 2018; Hunt, et al. 2020). En SAF con cobertura forestal reducida, se ha reportado clasificaciones con valores de precisión alrededor de 90% (Schmitt-Harsh et al. 2013; Sarmiento et al. 2014) y precisiones mayores en cultivo sin sombra (Mosomtai et al. 2020). En áreas con topografía homogénea se reportan clasificaciones con bajo nivel de error (Hebbar et al. 2019). Sin embargo, para sistemas con mayor densidad de árboles de sombra se reportan clasificaciones con errores en un rango de 10 a 30% (Schmitt-Harsh et al. 2013; Kelley et al. 2018; Tridawati et al. 2020). Sin embargo, estudios que integran datos espaciales de diferentes fuentes muestran una mayor precisión en la identificación de sistemas agroforestales de café. Maskell et al. (2021) demuestra la integración de datos ópticos y de radar para mapear diferentes sistemas de producción de café en Vietnam, logrando una alta precisión al distinguir entre varios tipos de café. Mukashema (2014) presenta un modelo de red bayesiano experto que combina datos espectrales y auxiliares para mapear con precisión campos de café a pequeña escala en Ruanda. Por otro lado, Mosomtai et al. (2020) explora el uso de conjuntos de datos satelitales de múltiples fuentes para mapear paisajes cafetaleros en Kenia, demostrando la utilidad de los datos de Sentinel-2 y generando métricas de paisaje para diferentes subzonas agroecológicas. En general, estos artículos enfatizan el potencial de la combinación de datos de teledetección de diferentes fuentes para mapear los SAF de café, permitiendo el monitoreo de los sistemas de producción y los cambios temporales de los mismos.

Justificación y preguntas de investigación

En Chiapas, hay una carencia de información sobre los tipos y distribución de sistemas agroforestales de café como consecuencia de la dispersión de las zonas de producción bajo prácticas agroforestales en regiones de alta marginación y difícil acceso. Debido a que el café representa una de las actividades económicas más importantes del estado y el 90% de la producción es bajo prácticas agroforestales, contar con información sobre los SAF es fundamental para entender los procesos de cambio del paisaje como resultado de la intervención antropogénica. Esta información es valiosa para monitorear la dinámica de deforestación y de la biodiversidad, así como para implementar estrategias de adaptación climática. Por otro lado, un mapeo preciso ayuda a estimar la producción y permite proponer modelos de pronóstico de la producción y una planificación sostenible (Souza et al. 2018). En general, el mapeo de agrosistemas de café proporciona una visión general de la importancia económica del café para municipios específicos.

Por otro lado, la composición del dosel y la densidad y distribución de las plantas de café en los SAF de café es modificado como respuesta a plagas y enfermedades, cambios en las condiciones climáticas de la región o con relación al contexto socioeconómico de los cafeticultores. Estas variaciones en la densidad y apertura de la cobertura forestal sobre las plantas de café en el sotobosque dificultan la identificación de los sistemas agroforestales, los cuales frecuentemente son confundidos con áreas de bosque, de acuerdo con diversos autores.

En esta investigación el objetivo principal es la caracterización de los SAF de café presentes en el área de mayor producción de café del estado a través del desarrollo de un enfoque basado en el uso de datos de percepción remota. Para ello, se plantea la evaluación de los cambios en la respuesta espectral temporal y la selección e incorporación de datos auxiliares en la clasificación a través de algoritmos computacionales.

El mapeo y caracterización de los diferentes sistemas agroforestales de café en Chiapas mediante teledetección no ha sido abordado, principalmente debido a las problemáticas relacionadas con las condiciones ambientales de la región y su efecto en las imágenes satelitales. Sin embargo, debido a los resultados mostrados en estudios donde hacen uso de datos multitemporales en otras regiones del planeta y a la información de campo disponible del área de estudio, este trabajo se enfocó la estructuración de un método computacional que permitiera identificar los SAF de café con un rango de error mínimo.

De este modo, las preguntas que busca responder esta investigación en relación con los desafíos que presenta el mapeo de sistemas agroforestales incluyen: A través de métodos de clasificación computacionales ¿es posible diferenciar entre sistemas agroforestales de café en el área de estudio? ¿El uso combinado de imágenes multitemporales y datos auxiliares permite el mapeo de SAF de café con rango de error menor del 10%? ¿Qué información proveniente de imágenes multiespectrales y multitemporales y datos auxiliaes es relevante para la identificación de diferentes tipos de sistemas agroforestales de café?

Esta investigación presenta una alternativa que permita generar mayor conocimiento sobre la dinámica de producción de café en el estado y contribuya al entendimiento del impacto y las implicaciones de la implementación de prácticas agroforestales en las áreas de bosque de la región y ayude desarrollo económico de ciudades pequeñas y a la permanencia de la población rural en las regiones cafetaleras a través de la planificación sostenible.

Objetivos

Objetivo general

Desarrollar un enfoque metodológico que permita identificar los tipos de sistemas agroforestales de café en una de las regiones de mayor producción ubicada en Chiapas mediante percepción remota.

Objetivos específicos

1. Caracterizar los sistemas agroforestales de café presentes en la región de estudio para el año 2019.
2. Identificar la información de percepción remota y datos auxiliares relevantes para el mapeo cada tipo de sistema agroforestal de café definido para el año 2019.
3. Generar un modelo computacional para el mapeo de SAF de café que procese los datos de percepción remota y e información complementaria relevantes para cada tipo de SAF identificado.

Artículo 1. Enviado a la revista Geocarto International, para la colección Geospatial Technologies for Understanding Complex Mountain Environments

Identification of coffee agroforestry systems using remote sensing data. A review of methods and sensor data.

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ABSTRACT

The current systematic review study focuses on an analysis of the computational methods used over the last twenty-two years to map coffee agroforestry systems (AFS). The objective was to evaluate the performance of classifiers used to map shade coffee in different physical conditions. A comparison is made through the implementation of the Kruskal-Wallis test using the accuracies reported. To do a valid comparison, five categories were generated to group the identified AFS. For the analysis, the algorithm, remote sensing data and supplementary information used were considered. For monocultures, the best performance was achieved using aerial photographs or multispectral images and parametric algorithms. For polycultures, less uncertainty is achieved when parametric algorithms are used. For Rustic AFS, the best results are obtained using object-based classifiers. Finally, the use of bands in the R (red), G (green), B (blue), and infrared ranges improve the identification of all types of coffee AFS.

KEYWORDS

Shade coffee; classifier; rustic; polyculture; monoculture;

1. Introduction

Agricultural land cover mapping has advanced significantly in the last decade due to the increased availability of information from remote sensors at different spatial scales, algorithms, and computing power for data processing. However, the identification of partially tree-covered land uses using remote sensing data still presents significant challenges, particularly in regions with high agrodiversity and heterogeneous topographic conditions (Philpot 2015; Jesus and Kuplich 2020; Li et al. 2014). It has been observed that topographic heterogeneity, structural complexity of cultivation systems, and the number of vegetation strata influence light reflectance and consequently, radiance scattering (Bense 2007). Additionally, the spatial resolution has implications on the pixels' values, as they can register information from more than one type of land cover, especially in fragmented landscapes (Lamparelli et al. 2012). All these considerations make it difficult to characterize spectral patterns and discriminate between different land cover classes or vegetation types. These may also increase uncertainty, particularly in those areas with an approximately similar spectral response (Rizvi et al. 2013). High spatial resolution images allow better visual differentiation of vegetation cover or land cover classes, which can reduce confusion in the classification process. However, the availability of this imagery is generally limited to small extensions, with low temporal resolution. In the case of radar images, signals are especially sensitive to surface dielectric properties, and surface component structure influences the backscattering of microwave signals, then the rugged topography of some mountainous crop areas limits the use of radar images (Podest 2017). Therefore, agriculture systems under forest cover, also known as agroforestry systems (AFS), are particularly complicated to map through remote sensing data due to the presence of two or more strata of vegetation above the crops and for the topographic conditions. These systems are widely implemented due to they provide a variety of socioeconomic and environmental benefits (Borelli et al. 2017). For example, the reduction of soil loss and water runoff, they serve as a carbon sink and contribute to biodiversity conservation (Beer et al. 2003), in response to the loss caused by the expansion and intensification of agriculture and livestock (Philpott and Bichier 2012; Figueroa-Hernández et al. 2015).

One of the main agricultural products grown through agroforestry systems is coffee. This system is adapted based on the environmental, cultural, and socioeconomic conditions of the growing areas as well as the needs and technical capacities of coffee growers (Borelli et al. 2017). On the other hand, in coffee-growing countries, coffee production represents an important part of the economy and national politics, in some cases is about 80% of the income (Figueroa-Hernández et al. 2015). However, mapping these production systems represents a challenge (Hailu et al. 2015; Kelley et al. 2018). Several studies show that the most frequent classification errors for agroforestry coffee systems correspond to the confusion of disturbed forests with secondary vegetation, and among different types of AFS (Kelley et al. 2018; Gomez et al. 2010; Tridawati et al. 2020).

To reduce uncertainty when creating a map of coffee production areas, is common the utilization of auxiliary data, such as digital elevation models, temperature or precipitation maps, which provide complementary information about the conditions of the area. This auxiliary data has been used when spectral data is not enough to discriminate between land cover classes. Due to the specific climate and soil requirements for each type of crop may help as additional context information in the mapping of coffee AFS. Most of the researchers have used as ancillary data texture descriptors, vegetation indices, climatic maps, and digital elevation models (Hunt et al. 2020).

Nevertheless, the particularities of each study area and the agroforestry practices implemented in each regions make it difficult to build universal mapping methods, so a review of the state of the art in coffee AFS mapping is critical for defining a discrimination method adjusted to each study area with the least possible uncertainty or confusion. This implies understanding how different remote sensing algorithms and data have responded under specific crop conditions, in order to identify remote sensing data and computational methods to better map different types of agroforestry systems.

In this work, an analysis of studies focused on the implementation of computational classifiers in coffee cultivation areas was conducted for evaluating the types of classifiers and the information that can be used to have less uncertainty in the resulting maps. This is according to the types of agroforestry coffee systems.

2. Materials and methods

The search was carried out in the Elsevier' Scopus, the Collection of Computer Science, World Wide Science and Web of Science databases on scientific articles published between 2000 and 2022 focused on mapping coffee agroforestry systems using remotely sensed data through computational methods. The search included articles in Spanish, English and Portuguese languages. The papers were selected if they included the three following topics: 1) fitting models from field data; 2) description of algorithms and remote sensing data used; and 3) at least two validation metrics (overall accuracy and producer's accuracy for the coffee class) of the resulting classification. In addition, studies that compared the performance between different classification algorithms or that make use of different remote sensing data using the same algorithm were also included. For these cases, each algorithm or implementation variation was considered as an individual case study. Subsequently, a database with the information extracted from each article was created (figure 1).

(Figure 1)

As a result of the systematic literature search, 161 articles were chosen according to the established selection filters. To determine if there are significant differences between the accuracy achieved by different mapping methods and type of agroforestry systems, an analysis of variance was carried out using the Kruskal-Wallis test (McKight and Najab 2010), since the samples in most of the studies did not present a normal distribution.

2.1. Definition of coffee agroforestry systems

Moguel and Toledo (1999), taking as a bases the degree of tropical disturbance, they classify agroforestry systems in the following categories,: 1) rustic, those systems with a low density of introduced coffee plants in natural vegetation, generally high plant diversity with at least three strata, and canopy coverage greater than 70%; 2) traditional polycultures, where there is a higher density of coffee plants, and species are introduced for exploitation purposes (e.g., fruit trees, medicinal plants, timber), pruning is frequent, two strata are maintained, and canopy coverage is between 40% and 70%; 3) commercial polycultures, defined as intensive coffee production systems, consequently, density is high, associated tree species diversity is low, all species have some exploitation purpose, and canopy coverage is in the range of 30% to 40%; 5) finally, shade-grown monocultures are systems where coffee is the only crop, and shade is provided by two or three tree species, regular pruning is applied, and canopy coverage is not greater than 30%. In this review, five types of agroforestry systems were defined based on those proposed by Moguel and Toledo. The objective was to make valid comparisons between the different cases found in the papers used in this. The new classification of coffee AFS have the following categories:

- Rustic. From (Moguel and Toledo 1999).
- Polycultures with vegetation cover of the tree layer greater than 45%.
- Polycultures with plant cover of the tree layer less than 45%.
- Monocultures with vegetation cover of the tree layer greater than 45%.
- Monocultures with plant cover of the tree layer less than 45%.

2.2. Computational methods used for mapping coffee production areas and metrics used for validation

Computational methods used for land cover classification can generally be divided into four phases: data gathering, preprocessing, selection and implementation of a classification algorithm and validation. Data gathering includes field data acquisition, photointerpretation, digitalization and imagery collection. Preprocessing includes radiometric, atmospheric, and topographic corrections, as well as geometric rectification. The choice and implementation of algorithms for mapping coffee areas is related to the study objective, available information, and the algorithms' ability to process input data. In this review, algorithms for mapping coffee agroforestry systems were categorized based on three criteria (Table 1).

(Table 1)

In the validation phase, usually, a confusion matrix is generated, from which validation metrics are obtained. The most common are commission and omission errors, overall accuracy, user and producer accuracy, and statistics such as the Kappa index, among others. In this systematic review, producer accuracy, user accuracy, and overall accuracy were considered as valid metrics to evaluate the performance of algorithms and the success of AFS mapping.

2.3. Remote sensing data and supplementary information used in the classification

Remote sensing data includes satellite information, manned and unmanned vehicle images. These data present a wide variety of spatial, temporal, radiometric, and spectral resolutions. The selection of images is defined according to user needs, image resolutions and scale. Another important factor to consider is the atmospheric conditions of the study area; in conditions of constant cloudiness, generally present in rain forests, the use of radar images is preferable due to the difficulty of obtaining high-quality data from optical sensors. In this review, sensor data was classified according to the spatial resolution of the images and a category was added for radar images. These groups are shown below:

- Low-resolution images (>20 m).
- Medium-resolution images (5-20 m).
- High-resolution images (<5 m).

- Radar images.

In coffee AFS mapping, complementary data is frequently used to improve accuracy or to address limitations of remote sensing data due to atmospheric conditions and considering type of analysis, for example, temporal crop change analysis, land use classification, among others. For this review, the complementary data found was grouped into the following categories:

- Land use maps.
- Soil type maps.
- Topographic maps, DEM, relief maps.
- Other maps.
- Statistical data, producer interviews, and field information.
- Texture descriptors.
- Vegetation indices.

3. Results

In the literature search, 61% of the studies were located in Brazil, 8% in Colombia, and the rest in 13 other countries. The total number of studies per country is shown in Figure 2.

(Figure 2)

It was found that 45% of the studies focused on the identification of agroforestry systems, 44% on spatially separating two types of systems, such as monocultures with different percentages of shade, and 11% on classifying three or more coffee AFS. When considering only the type of agroforestry system, polycultures were the most addressed systems, while rustic systems were the least analyzed. Table 2 shows the total number of case studies for each type of coffee system. Also, some studies apply different mapping approaches to the same study area or use the same algorithm for different regions. These studies were considered in more than one category.

(Table 2)

The case studies classified for the type of algorithms used are shown in Table 3, and the algorithms identified in the systematic review are shown in Figure 3. The Map Algebra category considered classifications carried out through visual interpretation assisted by tools included in GIS software such as ArcMap, QGIS, among others.

(Table 3)

(Figure 3)

The satellite images used in mapping AFS, classified by spatial resolution and sensor, are shown in Table 4. Landsat series images were the most used, probably due to high availability, temporal resolution, and no cost to the user.

(Table 4)

The auxiliary data identified is shown in Table 5. This data included information derived from satellite images and aerial photographs, such as vegetation indices and texture descriptors, thematic maps and topographic data. The category of Other maps includes precipitation maps, temperature maps, political boundaries, among others. In all cases where vegetation indices were used, NDVI was the most calculated, although in 44% of cases, it was combined with other indices.

(Table 5)

In the process of selection of case studies, we found that around 100 papers did not report values of accuracy by class or overall accuracy, so they were discarded. Additionally, many of the studies do not clearly report the process of defining training and validation datasets, so it is not possible to know if there are a sampling lacking independence and statistical robustness in obtaining the confusion matrix and validation metrics. Likewise, most case studies do not adjust the area by class, according to recommendations of Olofsson (2013; 2014), which would avoid bias in mapping. Table 6 shows case studies classified by validation process validation metrics.

(Table 6)

For each type of AFS, the producer, user, and overall accuracies are shown in Figure 4. The rustic system was the least addressed and had the lowest accuracy values. For polycultures, reported accuracy values varied less between case studies, and very similar overall accuracy values were obtained for both types of polycultures. Monocultures with shade coverage less than 45% show higher accuracy values compared to monocultures with a higher percentage of shade.

(Figure 5)

Table 7 shows the results of the Kruskal-Wallis test for all types of agroforestry systems. Coffee AFS with similar forest coverage do not show significant differences, while significant differences are observed between types of AFS with low coverage and coverage greater than 45%, whether monocultures, polycultures, or rustic systems.

(Table 7)

Monocultures (shade <45%) have been mostly analyzed through supervised classification algorithms, mainly Random Forest (RF), K-nearest neighbor (KNN), and Support Vector Machine (SVM). However, Object-Based Image Analysis (OBIA) and unsupervised classification methods such as ISOSEG and showed lower mean uncertainty and lower variation between reported producer accuracy values among studies, as shown in Figure 5.

(Figure 5)

Figure 6 shows that there are no significant differences in the approaches used to map this type of monoculture. The use of supervised and unsupervised methods does not show significant differences in the accuracies reported (Figure 6a). However, the analysis shows a much higher average accuracy for non-parametric algorithms than for parametric algorithms (Figure 6c), although they require more data for training and are computationally more expensive.

(Figure 6)

For the mapping of these monocultures, the use of Landsat, IKONOS, and SPOT-5 sensors showed similar accuracy values with the use of algorithms such as Maximum Likelihood (MAXVER) or Random Forest (RF), indicating that the spectral resolution of medium-resolution images can be an effective alternative for mapping monocultures when high-resolution images are not available (Figure 7). Most of the case studies did not use auxiliary information (Figure 8). However, analyzing those studies where complementary data is incorporated there is significant influence on mapping monoculture systems, according to validation metrics reported.

(Figure 7)

(Table 8)

On the other hand, Table 8 shows that there is no significant difference in the use of medium spatial resolution images compared to low- or high-resolution images, suggesting high-resolution images could be replaced with medium- or low-resolution images and get similar results.

(Figure 8)

In the analysis of monocultures with vegetation coverage greater than 45%, unsupervised classification showed higher producer accuracy than supervised methods. Spectral Mixture Analysis (SMA) algorithms reported the highest performance in unsupervised classifications, and MAXVER for the supervised category, as shown in Figure 9. However, the object-based analysis approach had lower uncertainty, as did monocultures with low shade (Figure 10b). The images used in both cases correspond to Landsat sensor images and high-resolution IKONOS images. Figure 10a shows a significant difference between supervised and unsupervised classification algorithms, although the producer accuracy means are very similar. The results shown in Figure 10b suggest that the sub-pixel analysis approach is more successful in mapping monocultures with coverage greater than 45% with a significant difference from the object and pixel approaches, resulting in a considerably higher producer accuracy mean than the other two approaches.

(Figure 9)

In some case studies where shade monocultures were analyzed, radar information from the Radarsat sensor was used, but it did not show a significant increase in mapping accuracy compared to studies that did not use radar data (Figure 11). In the analysis of variance for the use of optical and radar images, no significant differences were found between the types of images used, which is consistent with mapping monocultures with lower coverage, where the range of error is not dependent on the type of images or their spatial resolution, as shown in Table 9. According to the reported accuracies, for mapping these systems, the temporal resolution, that is, the analysis through changes in the spectral profiles, has a greater influence on mapping accuracy.

(Figure 10)

(Figure 11)

(Table 9)

On the other hand, incorporating digital elevation models into pixel-based analysis algorithms yielded similar commission and omission errors, also the mean accuracy values reported for the classification of vegetated monocultures did not show a significant variation when using this additional data or only satellite images (Figure 12).

(Figure 12)

For monocultures or coffee AFS in highly perturbed areas, the results reported suggest that high-resolution images provide significant information to increase classification accuracy, but using vegetation indices as an auxiliary to low-resolution images through object segmentation algorithms can perform better than using high-resolution images.

In the analysis of polycultures, it was found that the mapping error range increases with the percentage of shade, although the difference is not significant. Additionally, a high range of variation was observed between reported accuracies for different algorithms, compared to mapping monocultures (figure 13). Although a higher average producer accuracy value was observed for the Latent Multinomial Logit (LMNL) algorithm as an unsupervised classification method and the MAXVER algorithm for supervised classifications (Figure 14).

(Figure 13)

(Figure 14)

The Kruskal-Wallis analysis did not show a significant difference between supervised and unsupervised classifications (Figure 15) or the use of parametric and non-parametric algorithms (Figure 17) for both types of polycultures. However, the different approaches (Figure 16) for polycultures with a coverage greater than 45% do show a significant difference. The pixel-based analysis showed a higher producer accuracy mean than the object-based approach for polycultures with higher coverage. However, the analysis showed little variation between both types of polyculture, although the mean accuracy for less technified systems was distinctly lower (Figure 16).

(Figure 15)

(Figure 16)

(Figure 17)

For this type of AFS, a greater use of Landsat sensor images was found. The combination of imagery previously defined as low-resolution images with high-resolution images showed the highest accuracy values, compared to using only high-resolution images. Similarly, for monocultures, information in different spectral bands contributes more to classification performance than spatial resolution (Figure 18). Additional data used for case studies with lower reported error rates were topographic information (slope, elevation, among others) and information on vegetation in the study areas, such as vegetation indices and land use maps, as shown in Figure 19b.

(Figure 18)

(Figure 19)

Rustic systems were the least addressed, less than 5% of all reviewed studies. Reported accuracies varied in the range of 65 to 80% (Figure 4). Minimum pruning forest coverage and heterogeneous distribution of coffee plants made it difficult to identify these AFS. Therefore, different approaches from traditional methods are used for the classification of rustic systems. The use of rule-based algorithms, image segmentation and OBIA approaches through algorithms included in GIS analysis software were the only reported, as shown in Figure 20.

(Figure 20)

The analysis of variance for rustic agroforestry systems was developed only between parametric and non-parametric algorithms, which showed significant differences (Table 10). The mean producer accuracy between the two types of algorithms also differs considerably. Mapping through non-parametric algorithms showed a higher mean producer accuracy; because non-parametric algorithms do not assume a specific model, there is greater range of adjustment, generating a higher performance, i. e., more accurate results compared to algorithms with previously established parameters.

(Table 10)

In all reviewed studies, Landsat sensor images are used, with 50% of cases using auxiliary information from digital elevation models. The highest reported accuracies were reported using ISODATA algorithms that combine Landsat images with topographic data. However, the use of complementary data did not show a lower range of error, according to reported studies (Figure 21).

(Figure 21)

The systematic review showed pixel-based analysis through supervised classification algorithms was the most used method, with two main approaches: the use of high spatial resolution images and the multispectral analysis of low- and medium-resolution images. The use of high-resolution images had relative success in mapping areas with little forest cover or with a well-defined spatial distribution, i. e., with alleys between crops, spatial separation between types of vegetation and types of crops. Multispectral approach, on the other hand, had acceptable success for all types of AFS addressed in this review, although it requires greater knowledge of the ecosystems studied and greater computational capacities. The MAXVER algorithm is the most used along with RF, where commission and omission errors are low, but performance for global classification was lower than unsupervised classifications. On the other hand, the object-based approach showed high performance for detecting monocultures and polycultures with low forest coverage, but the highest producer accuracy values (above 85%) were obtained through the use of high-resolution images, consistent with Gaertner (2017), who compares a MAXVER pixel-based algorithm and an object-oriented SVM, and Bolanos (2009), who performs a similar comparison between pixel-based and object-oriented coffee crop mapping methods. The object-oriented analysis uses contextual information for assigning classes to pixels, reducing spectral variation between classes.

Additionally, auxiliary texture and contextual information can be derived from object segmentation (Liu and Xia 2010), so with high-resolution images, it is possible to access more contextual information, generating a lower range of uncertainty.

For mapping coffee AFS, the use of high spatial resolution images does not seem to have a significant improvement compared to the use of images with higher spectral resolution. This is mainly more noticeable in coffee crops with lower degrees of anthropization. According to the different cases studied, the use of bands in the R (red), G (green), B (blue), and infrared spectra seems to generate better separability of agroforestry systems. The reported accuracy of algorithm that used Sentinel 2 image is similar to Landsat and presents a smaller range of variation between studies. Hyperspectral images could contribute significantly to the mapping of complex agroforestry systems (Sharma et al. 2022), however, no studies were found in the review that made use of these images.

Radar images were rarely addressed in the studies included in this review. Only radar data in the C Band were used in the selected case studies. Because the SAR signal penetrates the first levels of vegetation, it is useful in mapping coffee AFS with little canopy or with a structure of only one level of shade trees, such as monocultures.

4. Discussion

The results suggest that analysis using different ranges of the electromagnetic spectrum can be applied to different types of AFS and identify coffee production areas with an acceptable range of error. In addition, the analysis of temporal changes in coffee reduced the confusion in mapping agroforestry systems and improved accuracy values for monocultures and polycultures, specifically through the use of images from different times of the year (Kelley et al. 2018; Tridawati et al. 2020; Ortega-Huerta et al. 2012). This is because the phenological changes of coffee affects the concentrations of chlorophyll *a* and *b* and the leaf area index (Marín-Garza et al. 2018; Castañeda-Castro 2018), cause changes in the spectral patterns of coffee areas, which are reflected in the optical images and the variability of vegetation index values, as shown in Júnior et al. (2013) and Bernardes et al. (2012).

The sub-pixel analysis approach was the least used in the selected studies, for monoculture mapping. The results imply that its use for less anthropized systems or with more complex topography can generate acceptable results if sufficient field information is available. However, one of the main challenges is the access to these areas and the acquisition of field information. Therefore, more robust algorithms or more complex spectral analysis techniques with auxiliary data and the combination of different sensors may have acceptable results. On the other hand, accuracy values suggest that the spatial organization of crop polygons and alleys allowed for better classification through methods that consider groups of pixels instead of individual pixels, i.e., object-oriented procedures. Although the use of auxiliary information to satellite images, mainly topographic data, increases the overall accuracy of classifications, the producer and user accuracy for monocultures and polycultures with little forest coverage do not show improvements compared to classifications that do not use additional information. For polycultures (shade >45%) and rustic systems, on the other hand, the highest per-class accuracies were obtained using vegetation indices derived from low-resolution and high-resolution images, such as NDVI and MSAVI, with robust learning algorithms like Random Forest.

The spectral response of coffee areas depends on factors such as crop density, management, and age of the coffee plants (Moreira et al. 2004). In addition, flowering and ripening do not develop uniformly (Damatta et al. 2007). This temporal and spatial variability is best represented through vegetation indices that highlight intrinsic attributes of plants related to the greenness and vigor of the agriculture areas (Baloloy et al. 2020). Moreover, several studies have addressed the variability of the coffee spectral response over the infrared range of the electromagnetic spectrum in relation to fruit ripening, which has provided a better identification of AFS (Escobar-López et al. 2022; Nogueira Martins et al. 2021). This could explain the higher accuracies obtained through vegetation indices, that is, spectral analysis compared to those focused on better spatial resolution.

Mapping coffee AFS is determined by the complexity of the systems and the topographic and vegetation conditions of the study area. For all types of agroforestry systems, mapping using information in different ranges of the electromagnetic spectrum obtained the lowest error values. However, for systems with little anthropogenic intervention, the use of robust parametric algorithms and ensembles with multispectral and multitemporal information is recommended, at least biennial cycles.

The proposed AFS classes are defined based on forest cover and density of coffee plants and shade trees, in order to be able to group the case studies. The future analysis could lead to a better definition of AFS classes, possibly expanding the number of classes or considering other variables.

On the other hand, the range of uncertainty in the precision values obtained is not reported in most of the study cases and the error due to the difference in areas between classes is not considered. This implies that the reported accuracies could have a considerable error range.

In addition, the comparison carried out for each type of agroforestry system was based on a single variable (type of algorithm, images used, auxiliary information, etc.). Future work could consider more than one variable and carry out a more exhaustive analysis.

5. Conclusions

The identification of coffee agroforestry systems should be based on the structural characteristics of the cultivation system. The distribution and abundance of coffee plants, canopy openness, tree distribution and abundance, and terrain conditions influence the information received by sensors, affecting algorithm performance. Limitations in accessing high spatial resolution or desired temporal resolution images can be addressed using data at different stages of the coffee phenological cycle and multispectral information. In mapping monocultures with little shade (<45% coverage) in highly disturbed production areas, better results were observed using aerial photographs or low-resolution multispectral images and parametric algorithms. Radar images could provide additional information when the canopy over coffee plants has a single layer.

For monocultures with more shade, multispectral images allow for better mapping of coffee agroforestry areas through algorithms such as MAXVER or Random Forest. Object-based segmentation can also be an option, considering topographic heterogeneity, where the use of texture descriptors reduces error in the classification of this type of agroforestry system.

The results showed that mapping polycultures with little shade (<45% coverage) presents less uncertainty when parametric algorithms are used, similar to the mapping of monocultures. The use of information from different ranges of the electromagnetic spectrum improves mapping accuracy in conjunction with complementary information such as texture descriptors when topographic heterogeneity is high.

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Notes on contributor(s)

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6. References

1. Baloloy AB, Blanco AC, Ana RRCS, Nadaoka K. 2020. Development and application of a new mangrove vegetation index (MVI) for rapid and accurate mangrove mapping. ISPRS Journal of Photogrammetry and Remote Sensing. 166:95–117. https://www.sciencedirect.com/science/article/pii/S0924271620301519.
2. Beer J, Harvey C, Ibrahim M, Harmaand JM, Somarriba E, Jiménez F. 2003. Servicios ambientales de los sistemas agroforestales. Agroforestería en las América. 10(37-28):80–87.
3. Bense T. 2007. Procesamiento de las imágenes satelitales. In: Sextas Jornadas de Educación en Percepción Remota en el Ámbito del Mercosur.
4. Bernardes T, Moreira MA, Adami M, Giarolla A, Rudorff BFT. 2012. Monitoring Biennial Bearing Effect on Coffee Yield Using MODIS Remote Sensing Imagery. Remote Sensing. 4(9):2492–2509. http://www.mdpi.com/2072-4292/4/9/2492.
5. Bolanos S. 2009. Using image analysis and GIS for coffee mapping. Library and Archives Canada= Bibliotheque et Archives Canada, Ottawa.
6. Borelli S, Conigliaro M, Olivier E. 2017. Agroforestería para la restauración del paisaje: Explorando el potencial de la agroforestería para mejorar la sostenibilidad y la resiliencia de los paisajes degradados. FAO.

7. Castañeda-Castro O. 2018. Variaciones en Área Foliar y Concentraciones de Clorofilas y Nutrimentos Esenciales en Hojas de Café Robusta (Coffea Canephora P.) Durante un Ciclo Anual. Agro Productividad. 11(4). http://www.revista-agroproductividad.org/index.php/agroproductividad/article/view/266.
8. Damatta FM, Ronchi CP, Maestri M, Barros RS. 2007. Ecophysiology of coffee growth and production. Brazilian Journal of Plant Physiology. 19:485–510.
9. Escobar-López A, Castillo-Santiago MA, Hernández-Stefanoni JL, Mas JF, López-Martínez JO. 2022. Identifying Coffee Agroforestry System Types Using Multitemporal Sentinel-2 Data and Auxiliary Information. Remote Sensing. 14(16):3847. Publisher: MDPI.
10. Figueroa-Hernández E, Pérez-Soto F, Godínez-Montoya L. 2015. La producción y el consumo del café. ECORFAN:64–82.
11. Gaertner J, Genovese VB, Potter C, Sewake K, Manoukis NC. 2017. Vegetation classification of Coffea on Hawaii Island using WorldView-2 satellite imagery. Journal of Applied Remote Sensing. 11(4):046005. Publisher: SPIE.
12. Gomez C, Mangeas M, Petit M, Corbane C, Hamon P, Hamon S, De Kochko A, Le Pierres D, Poncet V, Despinoy M. 2010. Use of high-resolution satellite imagery in an integrated model to predict the distribution of shade coffee tree hybrid zones. Remote Sensing of Environment. 114(11):2731–2744. Publisher: Elsevier.
13. Hailu BT, Maeda EE, Pellikka P, Pfeifer M. 2015. Identifying potential areas of understorey coffee in Ethiopia’s highlands using predictive modelling. International Journal of Remote Sensing. 36(11):2898–2919. https://www.tandfonline.com/doi/full/10.1080/01431161.2015.1051631.
14. Hunt DA, Tabor K, Hewson JH, Wood MA, Reymondin L, Koenig K, Schmitt-Harsh M, Follett F. 2020. Review of Remote Sensing Methods to Map Coffee Production Systems. Remote Sensing. 12(12):2041. https://www.mdpi.com/2072-4292/12/12/2041.
15. Jesus JBD, Kuplich TM. 2020. Applications of SAR data to estimate forest biophysical variables in Brazil. CERNE. 26(1):88–97. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S01047602020000100088&tlng=en.

16. Júnior AFC, de Carvalho Júnior OA, de Souza Martins O, Guerra AF. 2013. Phenological characterization of coffee crop (Coffea arabica L.) from MODIS time series. Brazilian Journal of Geophysics. 31(4):569–578.
17. Kelley LC, Pitcher L, Bacon C. 2018. Using Google Earth Engine to Map Complex Shade-Grown Coffee Landscapes in Northern Nicaragua. Remote Sensing. 10(6):952. http://www.mdpi.com/2072-4292/10/6/952.
18. Lamparelli RAC, Johann JA, Santos ÉRD, Esquerdo JCDM, Rocha JV. 2012. Use of data mining and spectral profiles to differentiate condition after harvest of coffee plants. Engenharia Agrícola. 32(1):184–196. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S010069162012000100019&lng=en&tlng=en.
19. Li M, Zang S, Zhang B, Li S, Wu C. 2014. A Review of Remote Sensing Image Classification Techniques: the Role of Spatio-contextual Information. European Journal of Remote Sensing. 47(1):389–411. https://www.tandfonline.com/doi/full/10.5721/EuJRS20144723.
20. Liu D, Xia F. 2010. Assessing object-based classification: advantages and limitations. Remote sensing letters. 1(4):187–194. Publisher: Taylor & Francis.
21. Marín-Garza T, Gómez-Merino FC, Aguilar-Rivera N, Murguía-González J, Trejo-Téllez LI, Pastelín-Solano MC, Castañeda-Castro O. 2018. Composición Bioactiva De Hojas De Café Durante Un Ciclo Anual. Revista Fitotecnia Mexicana. 41(4):365–372. http://167.172.243.173:80/index.php/RFM/article/view/121.
22. McKight PE, Najab J. 2010. Kruskal-Wallis test. The corsini encyclopedia of psychology:1–1. Publisher: Wiley Online Library.
23. Moguel P, Toledo V. 1999. Biodiversity Conservation in Traditional Coffee Systems of Mexico. Conservation Biology. 13(1):11–21.
24. Moreira MA, Adami M, Rudorff BFT. 2004. Análise espectral e temporal da cultura do café em imagens Landsat. Pesquisa Agropecuária Brasileira. 39(3):223–231. Publisher: SciELO Brasil.
25. Nogueira Martins R, de Carvalho Pinto FdA, Marcal de Queiroz D, Magalhaes Valente DS, Fim Rosas JT. 2021. A novel vegetation index for coffee ripeness monitoring using aerial imagery. Remote Sensing. 13(2):263. Publisher: MDPI.

26. Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA. 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment. 148:42–57. https://linkinghub.elsevier.com/retrieve/pii/S0034425714000704.
27. Olofsson P, Foody GM, Stehman SV, Woodcock CE. 2013. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sensing of Environment. 129:122–131. https://linkinghub.elsevier.com/retrieve/pii/S0034425712004191.
28. Ortega-Huerta MA, Komar O, Price KP, Ventura HJ. 2012. Mapping coffee plantations with Landsat imagery: an example from El Salvador. International Journal of Remote Sensing. 33(1):220–242. https://www.tandfonline.com/doi/full/10.1080/01431161.2011.
29. 591442.
30. Philpot W. 2015. Remote Sensing Fundamentals. Report No.
31. Philpott SM, Bichier P. 2012. Effects of shade tree removal on birds in coffee agroecosystems in Chiapas, Mexico. Agriculture, Ecosystems & Environment. 149:171–180. https://linkinghub.elsevier.com/retrieve/pii/S0167880911000533.
32. Podest E. 2017. Basics of Synthetic Aperture Radar (SAR). Pages: 1-56.
33. Rizvi RH, Dhyani SK, Newaj SA R, Karmakar PS. 2013. Mapping extent of agroforestry area through remote sensing: issues, estimates and methodology. Indian Journal of Agroforestry. 15(2):26–30.
34. Sharma P, Bhardwaj DR, Singh MK, Nigam R, Pala NA, Kumar A, Verma K, Kumar D, Thakur P. 2022. Geospatial technology in agroforestry: status, prospects, and constraints. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-022-20305-y.
35. Toledo VM, Moguel P. 2012. Coffee and Sustainability: The Multiple Values of Traditional Shaded Coffee. Journal of Sustainable Agriculture. 36(3):353–377. http://www.tandfonline.com/doi/abs/10.1080/10440046.2011.583719.
36. Tridawati A, Wikantika K, Susantoro TM, Harto AB, Darmawan S, Yayusman LF, Ghazali MF. 2020. Mapping the Distribution of Coffee Plantations from Multi-

Resolution, MultiTemporal, and Multi-Sensor Data Using a Random Forest Algorithm. Remote Sensing. 12(23):3933. https://www.mdpi.com/2072-4292/12/23/3933.

7. Figures

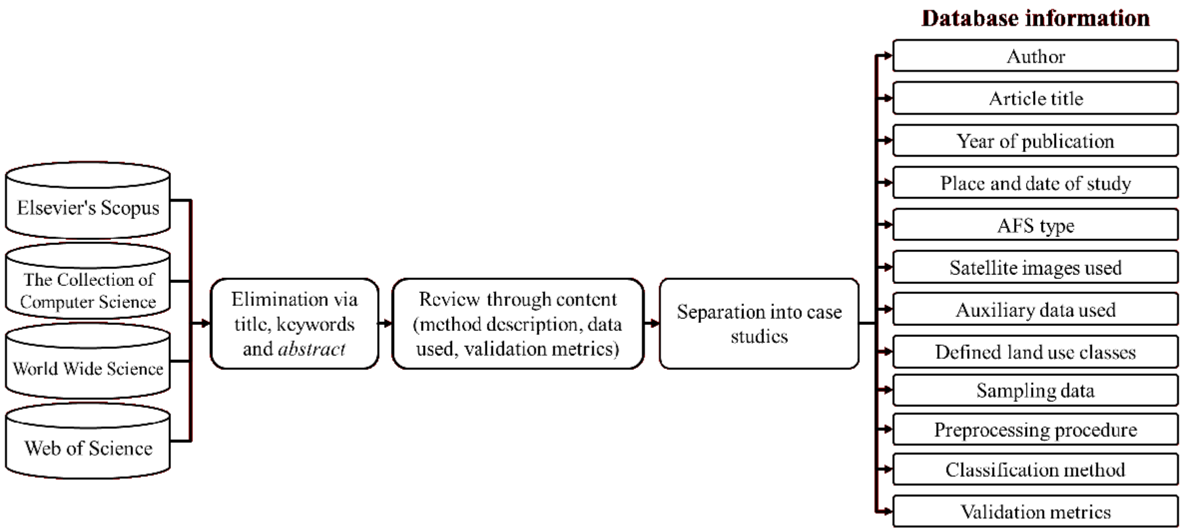
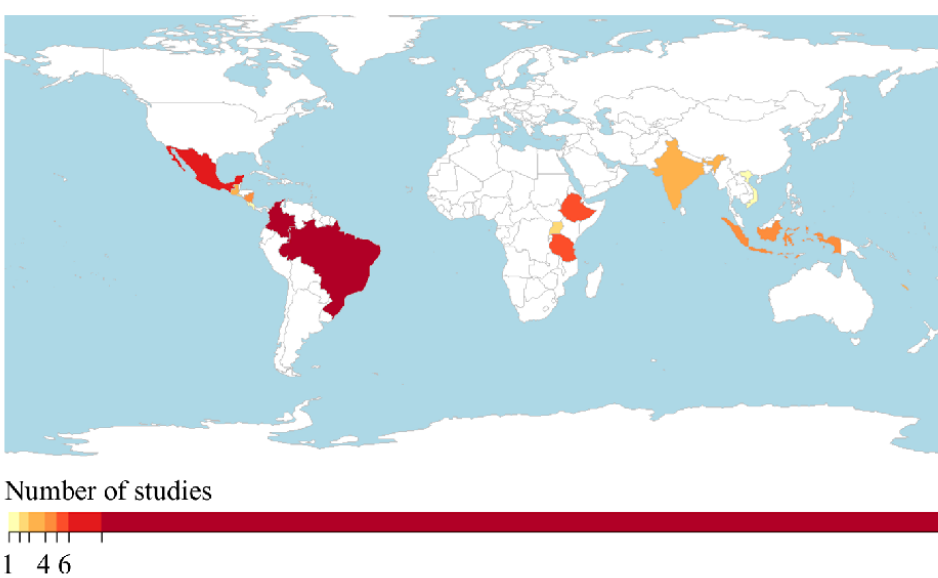


Figure 1. Process of the systematic review of literature for studies of coffee production areas.



Number of studies	Country
99	Brazil
13	Colombia
8	Mexico
6	Ethiopia
6	Tanzania
5	Indonesia
5	Nicaragua
4	Guatemala
4	New Caledonia
3	India
2	El Salvador
2	Hawaii
2	Uganda
1	Costa Rica
1	Vietnam

Figure 2. Map of the studies selected by country.

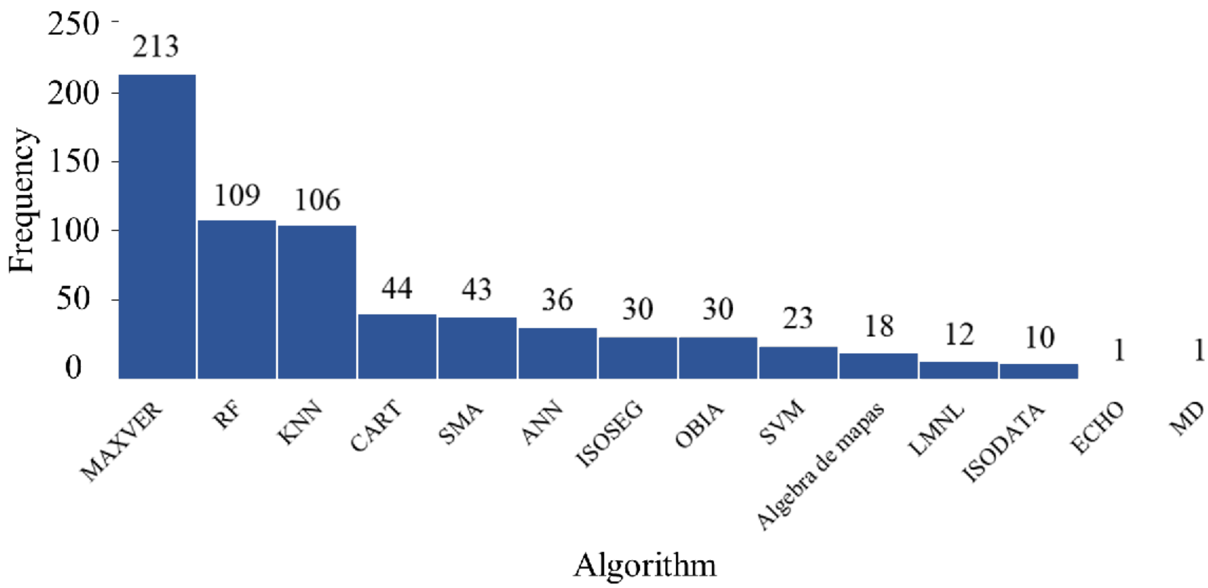


Figure 3. Algorithms identified for the classification of coffee agroforestry systems. MAXVER = Maximum likelihood; RF = Random Forest; KNN = K-Nearest Neighbor; CART = Classification and Regression Tree; SMA = Spectral Mixture Analysis; ANN = Artificial Neuronal Network; ISOSEG = Per-field clustering classifier; OBIA = Object-Based Image Analysis; SVM = Support Vector Machine; LMNL = Multinomial Logit; ISODATA = Iterative Self-Organizing Data Analysis; ECHO = Extraction and Classification of Homogeneous Objects; MD = Minimum Distance.

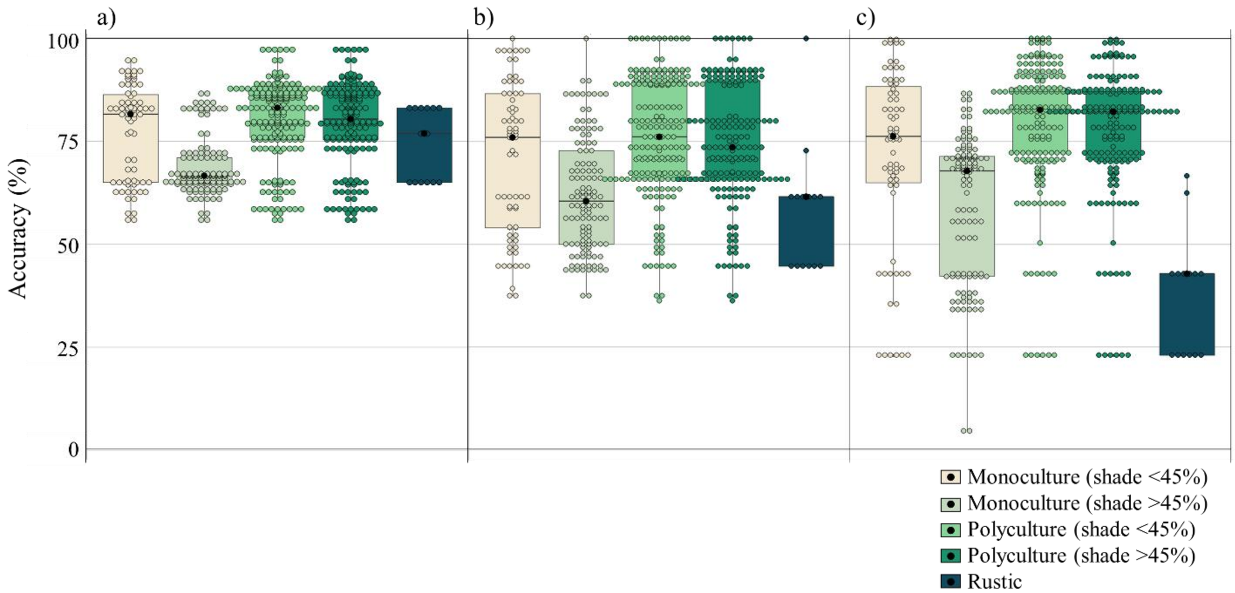


Figure 4. Accuracies achieved by type of agroforestry system. a) Global accuracy, b) Producer accuracy and c) User accuracy.

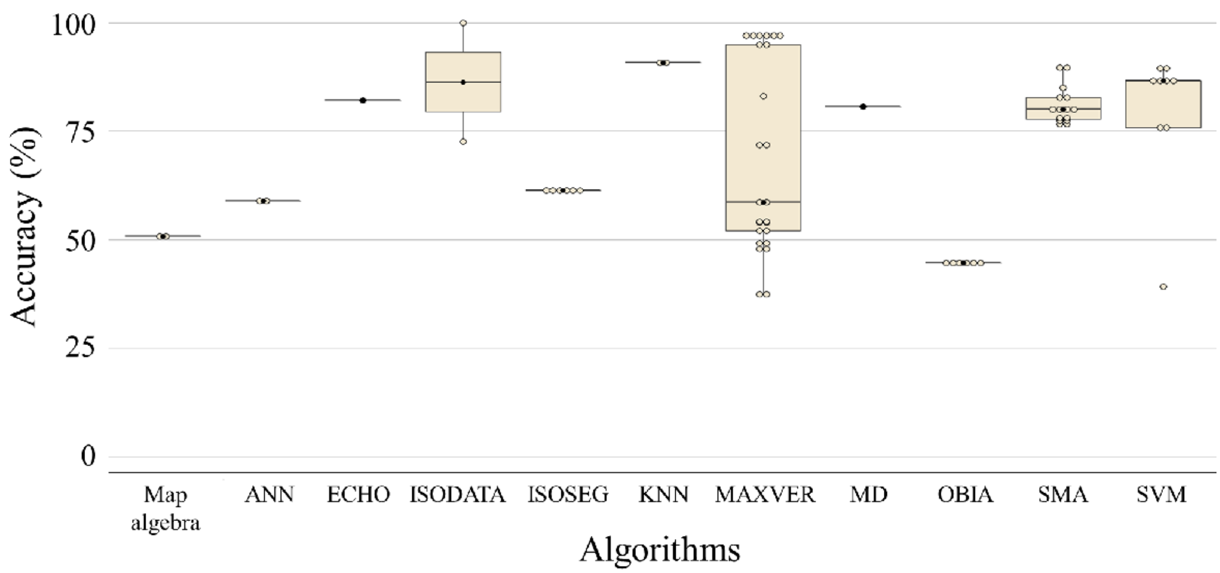


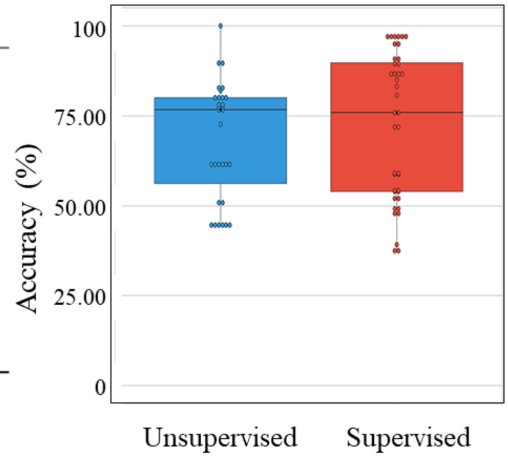
Figure 5. Accuracies achieved by type of agroforestry system. a) Global accuracy, b) Producer accuracy and c) User accuracy.

Kruskal-Wallis

Chi-square = 1.1157
P-value = 0.2908

Multiple comparison test after Kruskal-Wallis

	Comparisons		
	Observed difference	Critical difference	Difference
Unsupervised - Supervised	5.21	9.68	No significant

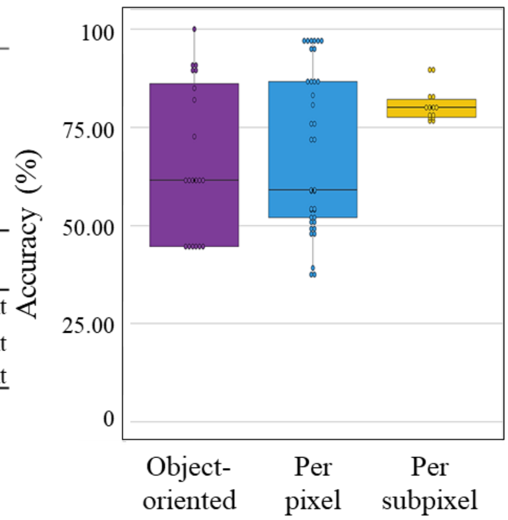


Kruskal-Wallis

Chi-square = 3.5696
P-value = 0.1678

Multiple comparison test after Kruskal-Wallis

	Comparisons		
	Observed difference	Critical difference	Difference
Object oriented - Per pixel	1.67	13.71	No significant
Object oriented - Per subpixel	12.56	17.22	No significant
Per pixel - Per subpixel	10.89	15.50	No significant



Kruskal-Wallis

Chi-square = 2.4178
P-value = 0.12

Multiple comparison test after Kruskal-Wallis

	Comparisons		
	Observed difference	Critical difference	Difference
Non parametric - parametric	7.78	9.82	No significant

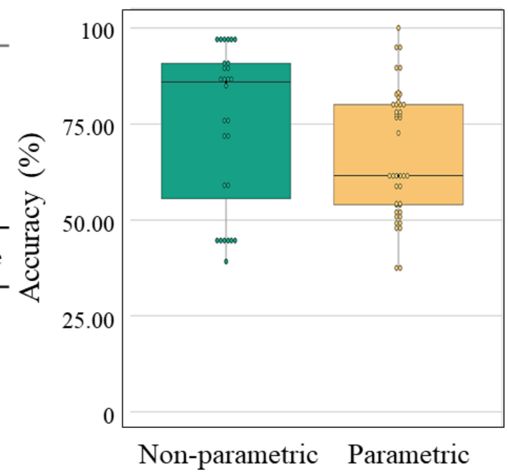


Figure 6. Analysis of variance and producer accuracy by a) whether it use training data, b) analysis unit and c) whether it use statistical parameters for mapping monocultures (shade <45%).

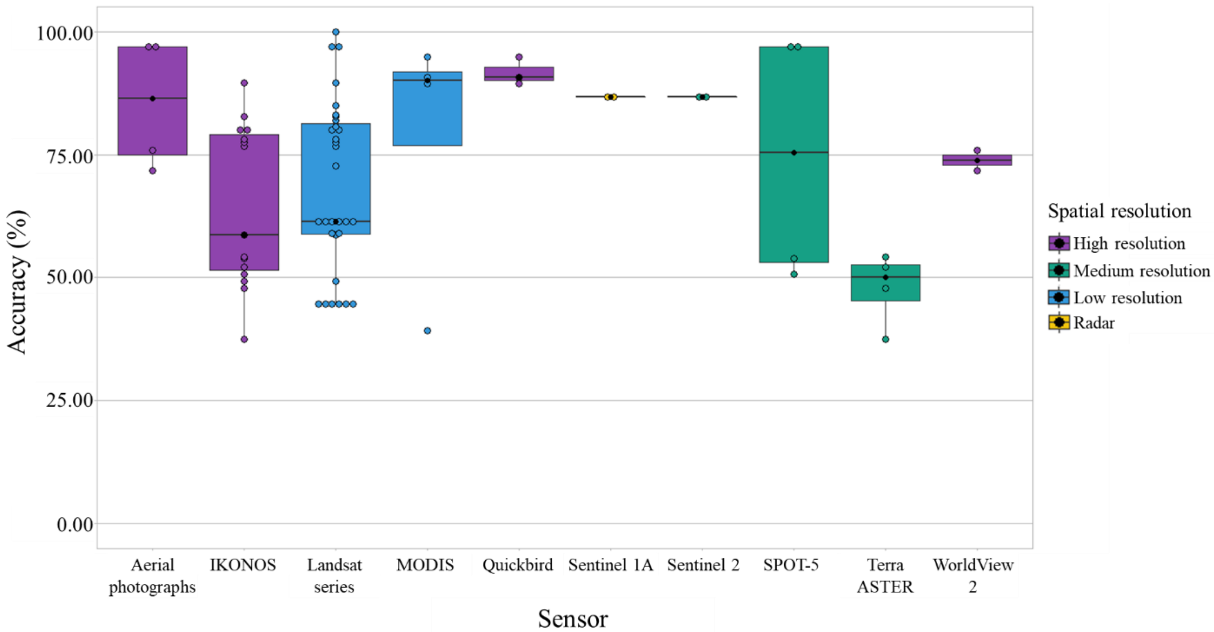


Figure 7. Producer accuracy for mapping shaded monocultures (shade <45%) by sensor type.

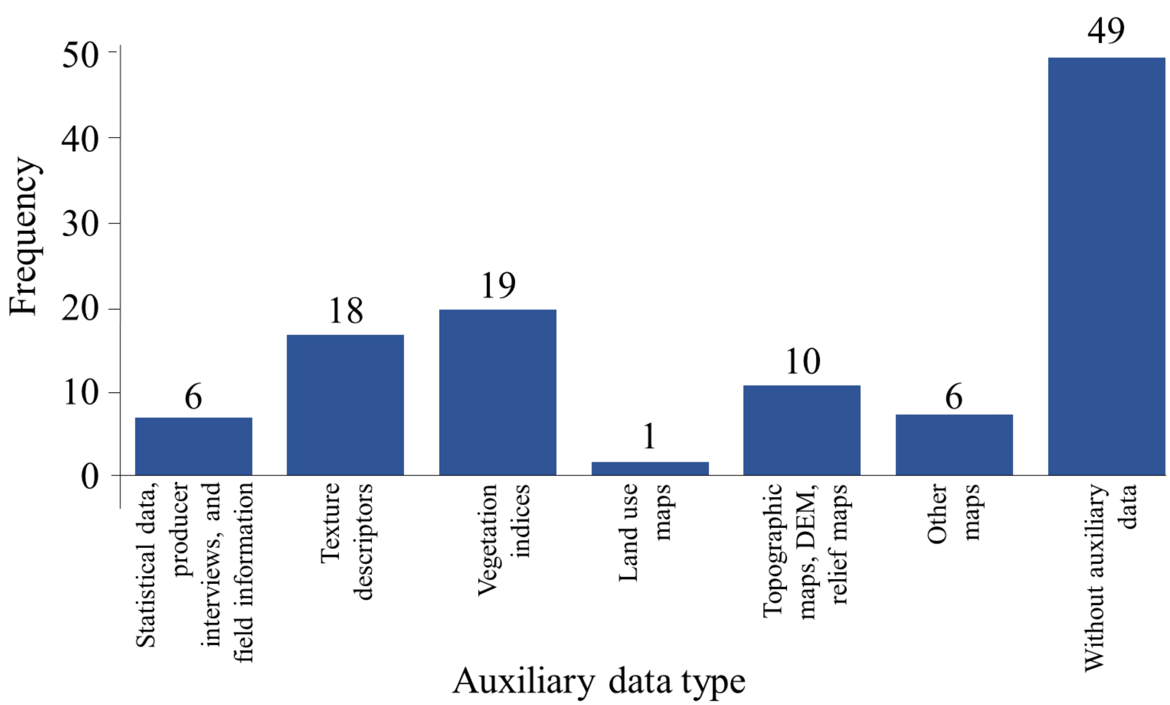


Figure 8. Auxiliary information used for the classification of monocultures (shade <45%).

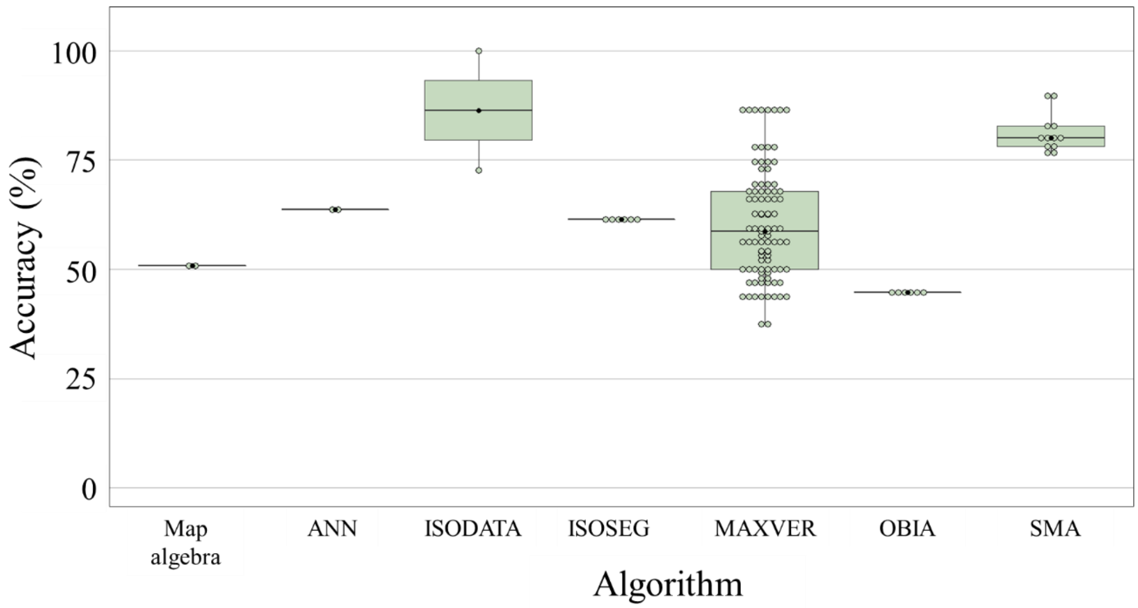


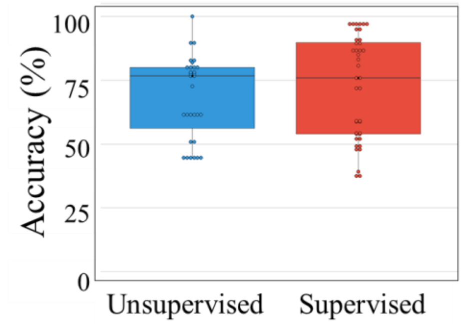
Figure 9. Reported producer accuracy for coffee monoculture (shade >45%) by algorithm type.

Analysis of variance by type of classification

a) Multiple comparison test after Kruskal-Wallis

Chi-square = 3.9918
P-value = 0.04572

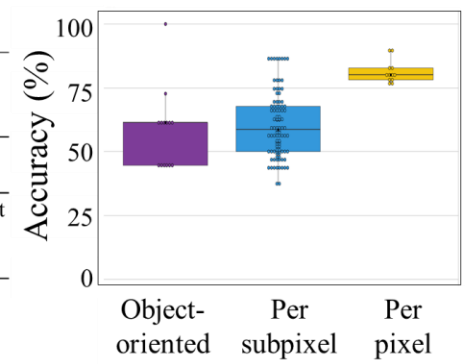
Comparisons	Observed difference	Critical difference	Difference
Unsupervised - Supervised	15.41	15.3	No significant



b) Multiple comparison test after Kruskal-Wallis

Chi-square = 24.217
P-value = $5.513e^{-06}$

Comparisons	Observed difference	Critical difference	Difference
Object oriented - Per pixel	9.18	24.58	No significant
Object oriented - Per subpixel	60.81	33.85	Significant
Per pixel - Per subpixel	51.63	26.31	Significant



c) Multiple comparison test after Kruskal-Wallis

Chi-square = 1.3389
P-value = 0.2472

Comparisons	Observed difference	Critical difference	Difference
Non-parametric - Parametric	15.23	17.10	No significant

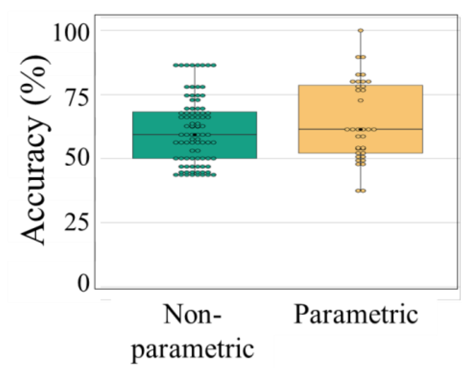


Figure 10. Analysis of variance and producer accuracy by a) type of classification, b) analysis unit and c) whether it use statistical parameters for mapping coffee monocultures (shadow >45%).

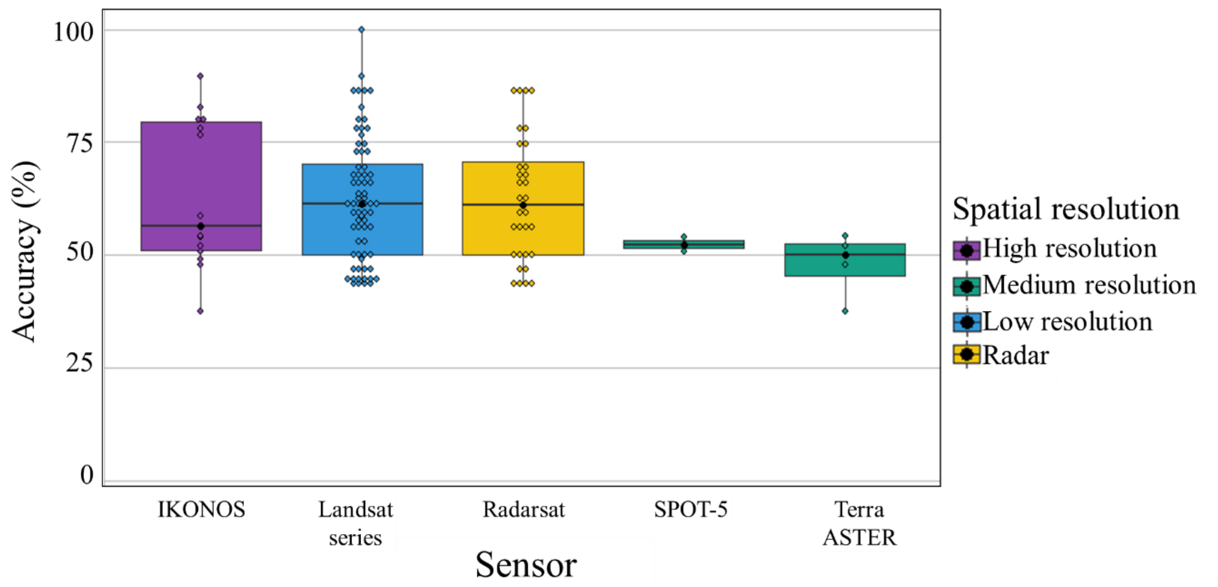


Figure 11. Reported producer accuracy for monocultures (shade >45%) by sensor type.

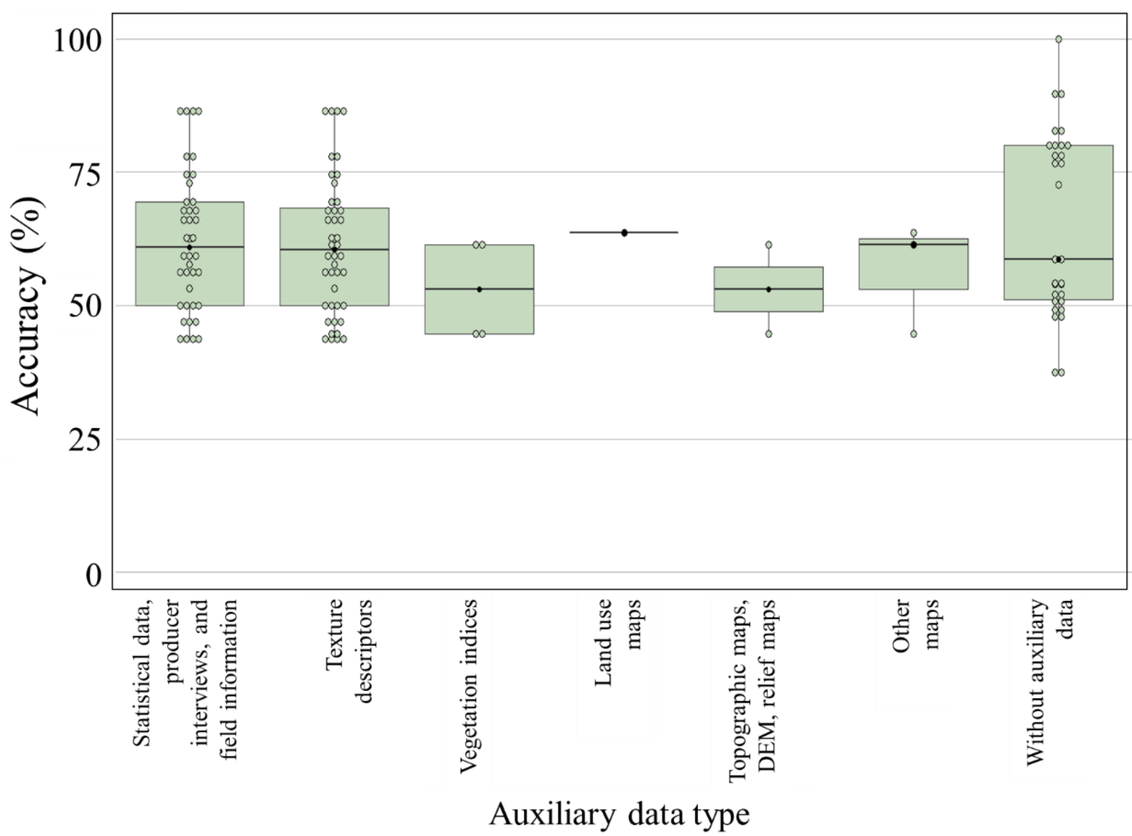


Figure 12. Producer accuracy for mapping shaded monoculture mapping (shade >45%) by type of auxiliary data used.

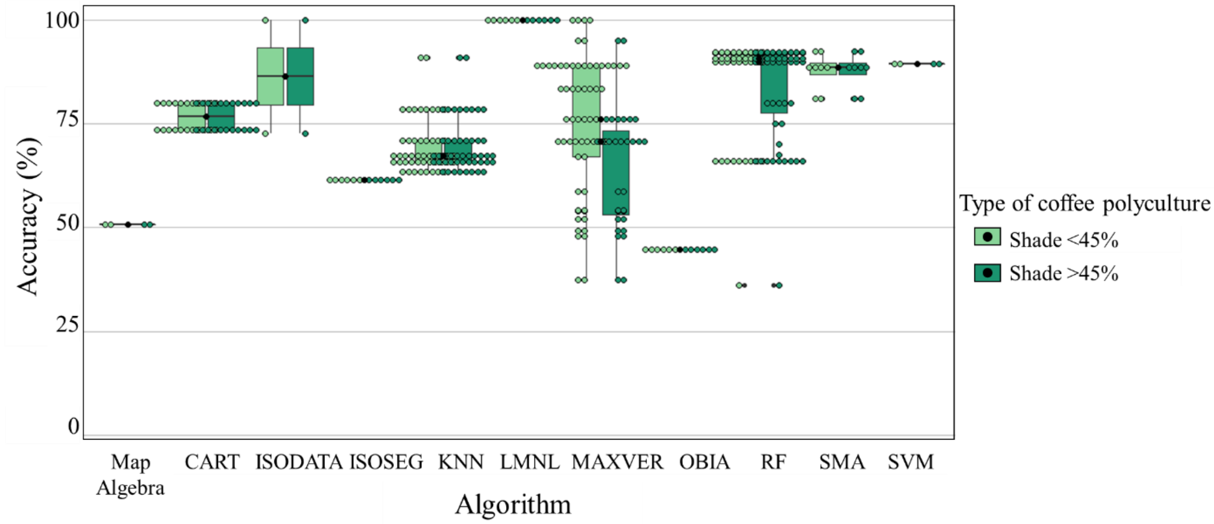


Figure 13. Producer accuracy reported for polyculture mapping by algorithm.

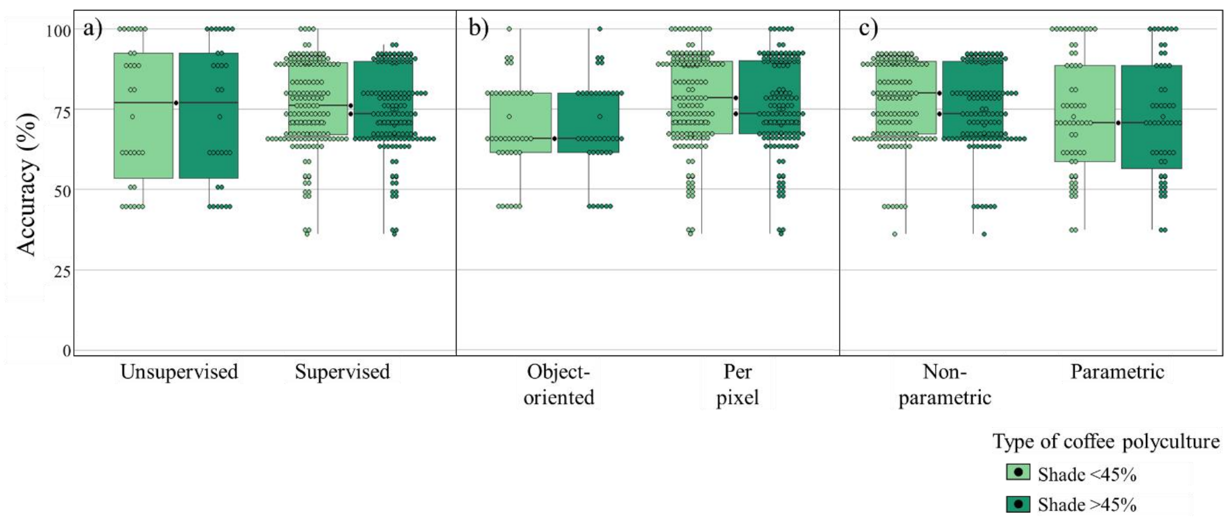


Figure 14. Producer accuracy reported for polyculture mapping by algorithm type: a) by supervised or unsupervised classification, b) by analysis unit, and c) whether it is possible to adjust algorithm parameters.

Analysis of variance by type of algorithm
(whether it use training data)

Multiple comparison test after Kruskal-Wallis
Polyculture (shade <45%)

Chi-square = 1.1157
P-value = 0.2908

Comparisons	Observed difference	Critical difference	Difference
Unsupervised - Supervised	5.21	9.68	No significant

Multiple comparison test after Kruskal-Wallis
Polyculture (shade >45%)

Chi-square = 0.049954
P-value = 0.8231

Comparisons	Observed difference	Critical difference	Difference
Unsupervised - Supervised	2.42	21.24	No significant

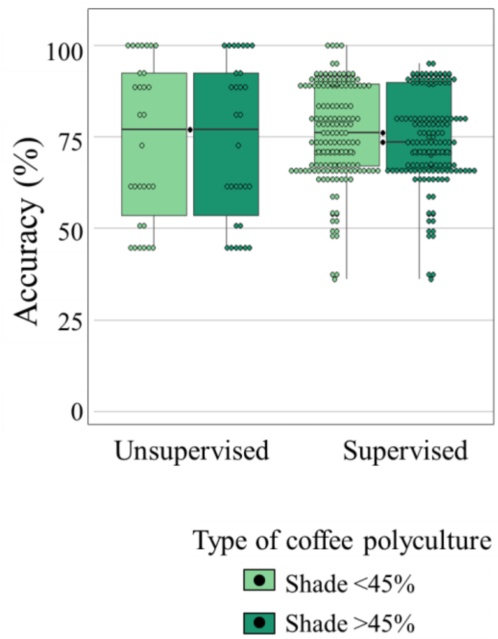


Figure 15. Kruskal-Wallis analysis of variance for supervised and unsupervised classification for mapping polycultures with different shade coverage percentages.

Analysis of variance for object-oriented and per-pixel algorithms in polyculture mapping

Multiple comparison test after Kruskal-Wallis
Polyculture (shade <45%)

Chi-square = 3.5696
P-value = 0.1678

Comparisons	Observed difference	Critical difference	Difference
Object-oriented - Per pixel	1.67	13.71	FALSE
Object-oriented - Per subpixel	12.56	17.22	FALSE
Per pixel – Per subpixel	10.89	15.50	FALSE

Multiple comparison test after Kruskal-Wallis
Polyculture (shade >45%)

Chi-square = 8.3335
P-value = 0.003892

Comparisons	Observed difference	Critical difference	Difference
Object-oriented - Per pixel	27.96	19.00	TRUE

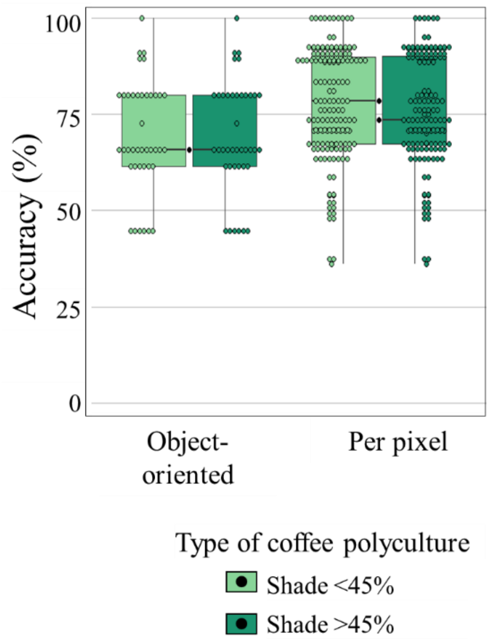


Figure 16. Kruskal-Wallis analysis of variance for object-oriented and per-pixel classifications for mapping polycultures with different shade coverage percentages.

Analysis of variance for parametric and non-parametric algorithms in polyculture mapping

Multiple comparison test after Kruskal-Wallis
Polyculture (shade <45%)

Chi-square = 2.4178
P-value = 0.12

Comparisons	Observed difference	Critical difference	Difference
Non-parametric - Parametric	7.78	9.82	FALSE

Multiple comparison test after Kruskal-Wallis
Polyculture (shade >45%)

Chi-square = 3.0539
P-value = 0.08054

Comparisons	Observed difference	Critical difference	Difference
Non-parametric - Parametric	15.23	17.10	FALSE

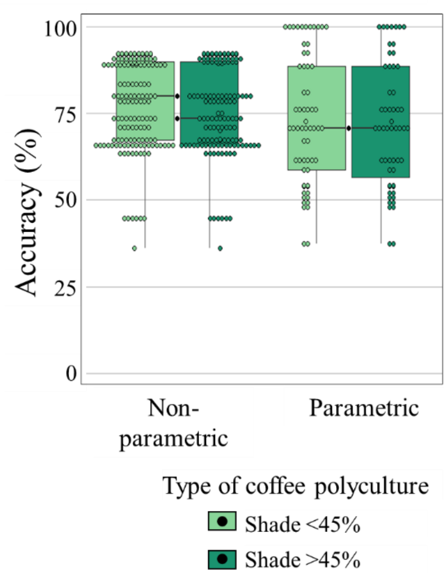


Figure 17. Kruskal-Wallis analysis of variance for parametric and non-parametric algorithms for mapping polycultures with different shade coverage percentages.

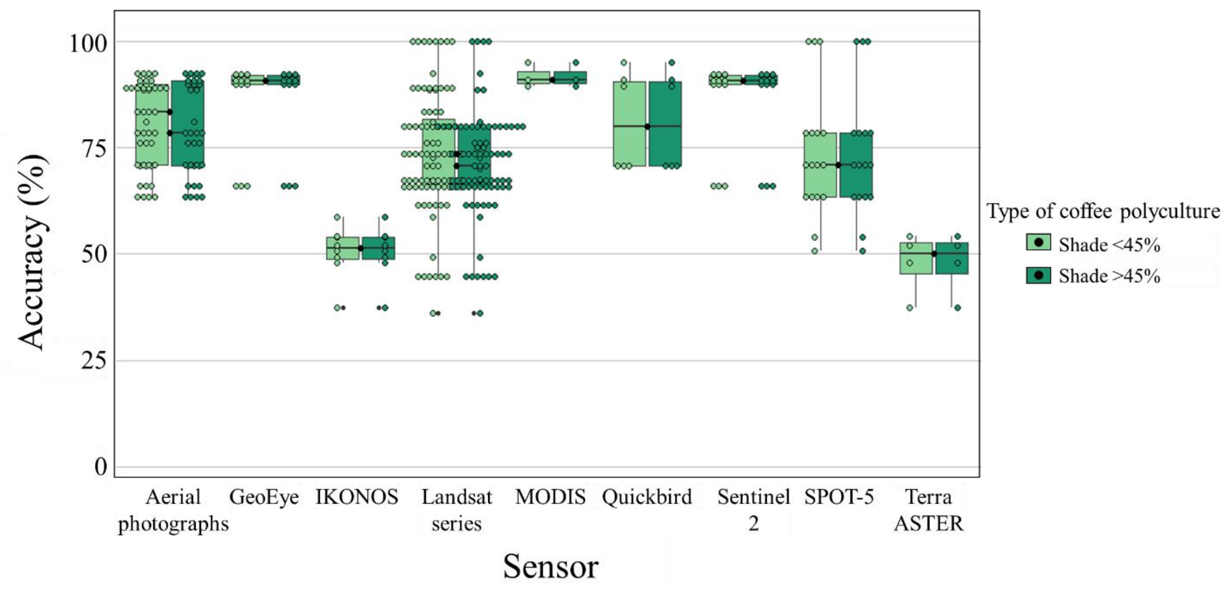


Figure 18. Producer accuracy reported for polycultures by sensor type.

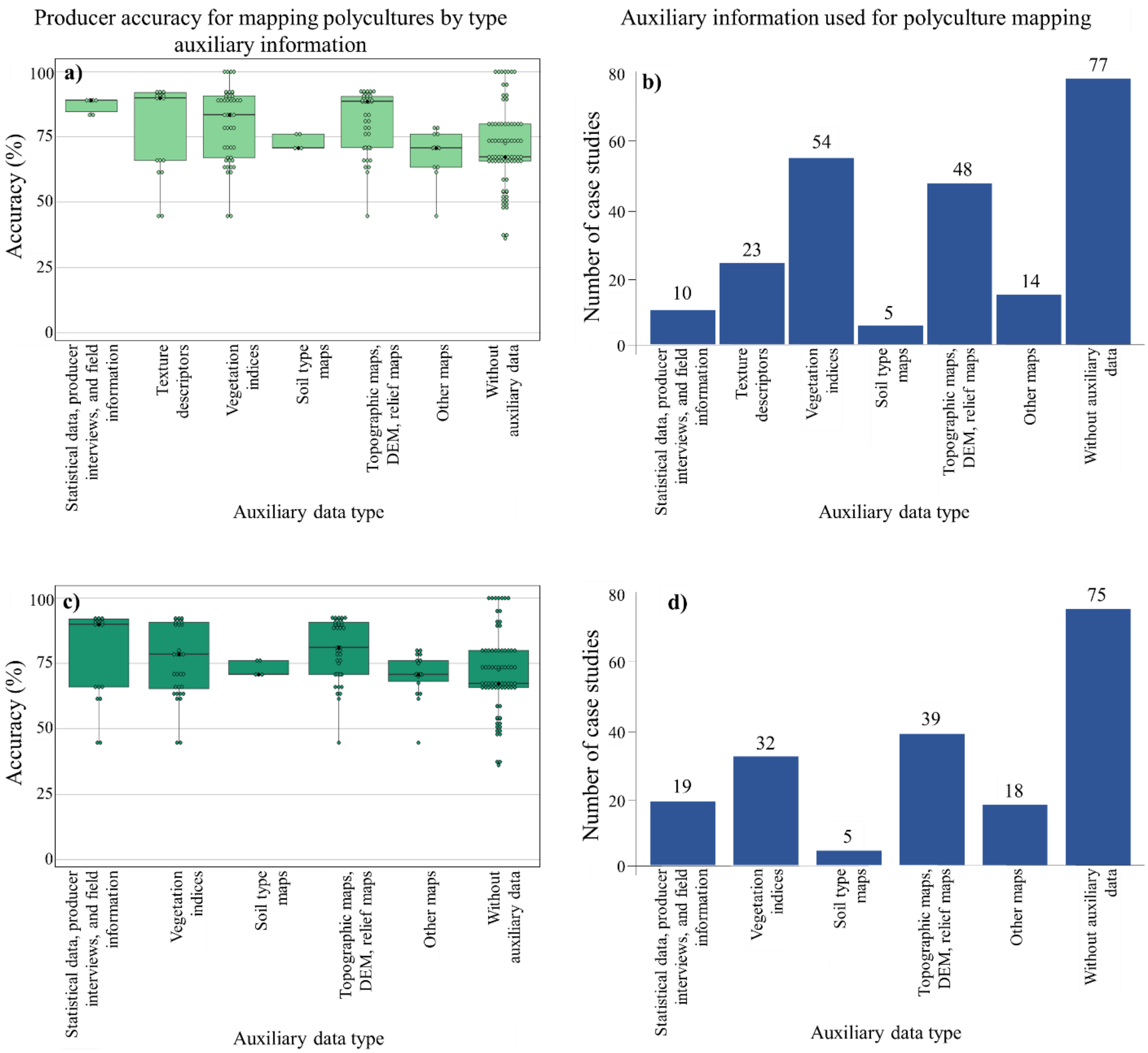


Figure 19. a) Producer accuracy reported by type of auxiliary data used and b) number of case studies by type of auxiliary data used for polycultures (shade <45%); and c) global accuracy reported by type of auxiliary data used and d) number of case studies by type of auxiliary data used for polycultures (shade >45%).

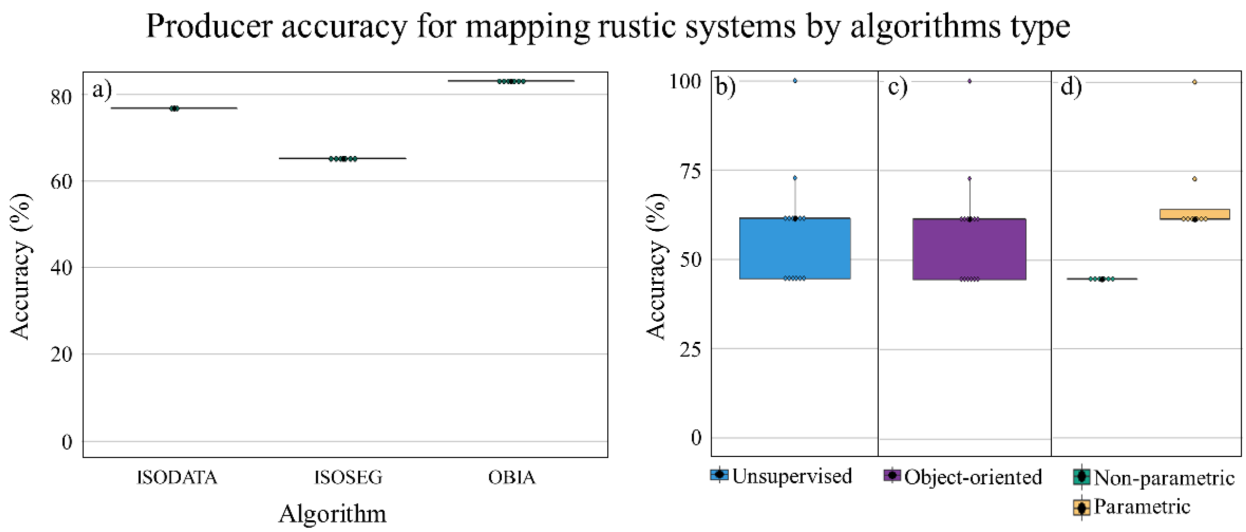


Figure 20. Producer accuracy reported for mapping of rustic systems by a) algorithm, b) by supervised or unsupervised classification, c) by analysis unit and d) whether it is possible to adjust algorithm parameters.

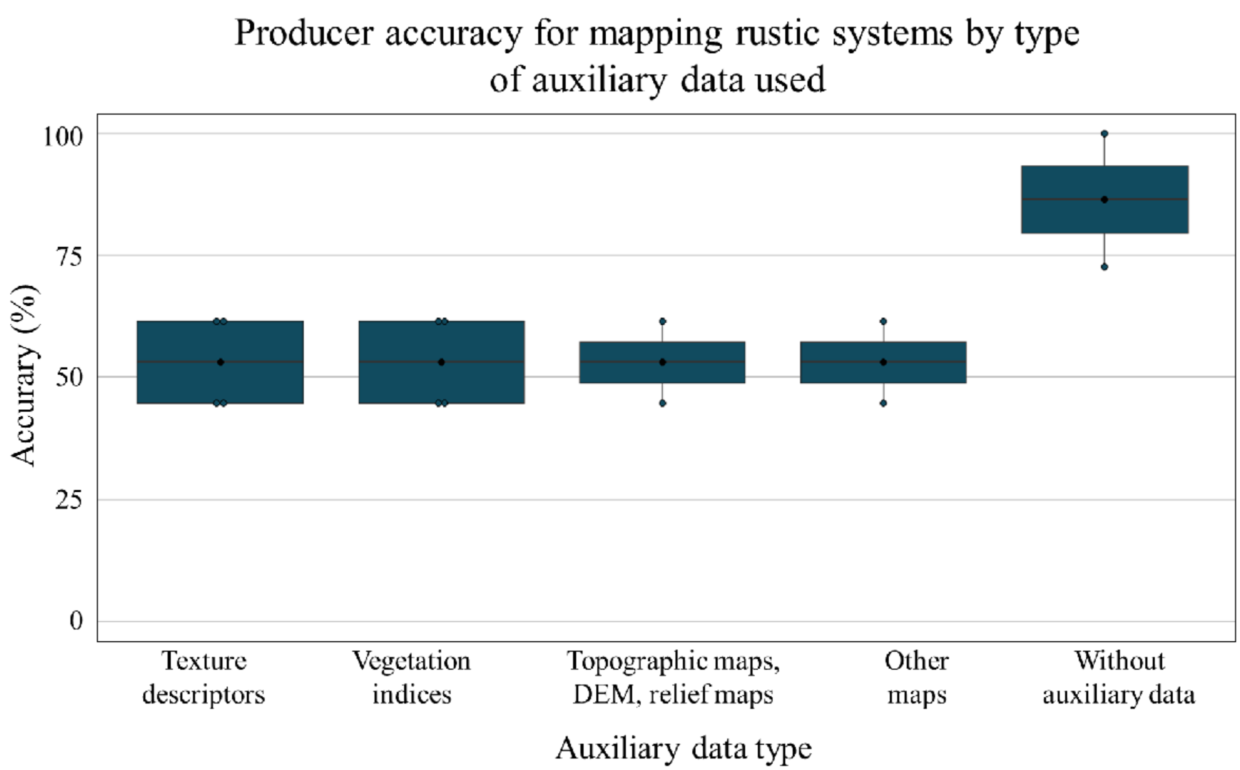


Figure 21. Producer accuracy for mapping rustic systems by type of auxiliary data used.

8. Tables

Table 1. Criteria for classification of AFS mapping algorithms.

Type of classification	Category	Attributes
Classification approach	Supervised classification	Land use classes are defined by the user. There are enough reference data that are used as training samples for the generation of thematic maps.
	Unsupervised classification	The information within the images is grouped into various spectral classes. The user labels and merges the generated classes according to the object of study.
Analysis unit	Per subpixel	The value of each pixel is considered a linear or non-linear combination of different spectral response and there is a proportional membership of the pixel to different classes.
	Per pixel	The algorithms combine the pixel information according to a defined characteristic, ignoring mixed pixel conflicts.
	Object-oriented	Images are segmented by aggregating pixels into objects, and classification is done based on these objects instead of classifying individual pixels.
Statistical approach	Parametric	They use statistical parameters (covariance matrix, mean vector, etc.) from training sites. A Gaussian distribution is generally assumed.
	Non-parametric	No assumptions are made about the data and it does not use statistical parameters.

Table 2. Case studies by type of AFS found.

Type of AFS	Rustic	Polyculture (shade >45%)	Polyculture (shade <45%)	Monoculture (shade >45%)	Monoculture (shade <45%)
Number of studies	6	91	96	49	47

Table 3. Case studies by type of AFS found.

Type of classification	Category	Number of studies
Classification approach	Supervised classification	138
	Unsupervised classification	23
Analysis unit	Per subpixel	7
	Per pixel	121
	Object-oriented	33
Statistical approach	Parametric	46

	Non-parametric	115

Table 4. Frequency of identified satellite images.

Type of satellite images	Sensor	Number of studies
Low-resolution imagery (>20 m)	IRS - Resourcesat LISS IV	1
	IRS – LISS III	1
	Landsat series	118
	MODIS	7
Medium-resolution imagery (5-20 m)	SPOT series	12
	Sentinel 2	11
	Terra ASTER	4
High-resolution imagery (< 5 m)	UAV / Aerials	19
	Quickbird	11
	WorldView 1 y 2	2
	IKONOS	15
	Cartosat 1	1
	GeoEye	5
Radar imagery (C-Band)	Sentinel 1	6
	Radarsat	16

Table 5. Auxiliary data used in case studies.

Type of auxiliary data	Number of studies
Land use maps	10
Soil type maps	3
Topographic maps, DEM, relief maps	30
Other maps	9
Statistical data, producer interviews, and field information	32
Texture descriptors	44
Vegetation indices	36
Without auxiliary data	94

Table 6. Case studies classified by reported accuracy evaluation metrics.

Reported accuracy evaluation metrics	Global accuracy only	Global accuracy and Kappa index	Overall accuracy, Kappa index and class accuracy
Number of studies	6	12	143

Table 7. Analysis of variance by type of AFS and producer accuracy reported.

Multiple comparison test after Kruskal-Wallis

Chi-square = 82.524
P-value < 2.2xe-16

Comparisons	**Observed difference**	**Critical difference**	**Difference**
Monoculture (shade <45%) - Monoculture (shade >45%)	99.02	73.14	Significant
Monoculture (shade <45%) - Polyculture (shade >45%)	59.40	67.51	No significant
Monoculture (shade <45%) - Polyculture (shade >45%)	41.82	68.46	No significant
Monoculture (shade <45%) - Rustic	147.28	143.72	Significant
Monoculture (shade >45%) - Polyculture (shade >45%)	158.41	55.71	Significant
Monoculture (shade >45%) - Polyculture (shade >45%)	140.84	56.86	Significant
Monoculture (shade >45%) - Rustic	48.26	138.56	No significant
Polyculture (shade <45%) - Polyculture (shade >45%)	17.57	49.40	No significant
Polyculture (shade <45%) - Rustic	206.67	135.68	Significant
Polyculture (shade >45%) - Rustic	189.1	136.15	Significant

Table 8. Analysis of variance by spatial resolution and producer accuracy achieved for mapping of monocultures (shade <45%).

Multiple comparison test after Kruskal-Wallis

Chi-square = 1.98
P-value = 0.5766

Comparisons	**Observed difference**	**Critical difference**	**Difference**
High resolution – Low resolution	1.70	14.43	No significant
High resolution – Medium resolution	4.36	20.50	No significant
Low resolution – Medium resolution	2.66	19.52	No significant

Table 9. Analysis of variance by spatial resolution of the images used and produces accuracy achieved for monocultures (shade >45%).

Multiple comparison test after Kruskal-Wallis

Chi-square = 5.0634
P-value = 0.1672

Comparisons	**Observed difference**	**Critical difference**	**Difference**
High resolution – Low resolution	1.99	27.70	No significant
High resolution – Medium resolution	35.57	46.27	No significant
High resolution – Radar	2.70	30.38	No significant
Low resolution – Medium resolution	33.58	40.29	No significant

Low resolution – Radar	0.71	20.15	No significant
Medium resolution – Radar	32.88	42.18	No significant

Table 10. Analysis of variance of parametric and non-parametric algorithms and producer accuracy reported for mapping of rustic AFS mapping.

Multiple comparison test after Kruskal-Wallis

Chi-square = 11.345
P-value = 0.0007563

Comparison	Observed difference	Critical difference	Difference
Non-parametric - Parametric	35.46	29.53	Significant

Artículo 2. Publicado en Remote Sens. 2022, 14(16), 3847, Special Issue Novel Approaches in Tropical Forests Mapping and Monitoring – Time for Operationalization

Identifying coffee agroforestry system types using multitemporal sentinel-2 data and auxiliary information

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Abstract: Coffee is one of the most important agricultural commodities of Mexico. Mapping coffee land-cover is still a challenge because it is grown mainly on small areas in agroforestry systems (AFS), which are located in hard-to-access mountainous regions. The objective of this research was to map coffee AFS types in a mountainous region using the changing spectral response patterns over the dry season as well as supplementary data. We employed Sentinel-2 images, a digital elevation model, soil moisture layers, and 150 field plots. First, we defined three coffee AFS types based on their structural and spectral characteristics. Then, we performed a recursive feature elimination analysis to identify the most relevant predictor variables for each land use/cover class in the region. Next, we constructed a predictor variable dataset for each AFS type and one for the remaining land use/cover classes. Afterward, four maps were generated using a Random Forest (RF) classifier. Finally, we combined the four maps into a unique land-cover map through a maximum likelihood algorithm. Using a validation sample of 300 sites derived from Planet images (4.5 m pixel size), we estimated a 96% map overall accuracy. Two AFS types were classified as with low error; the third, with the highest tree density, had the lowest accuracy. The results obtained show that the infrared and near-infrared bands from the Sentinel-2 scenes are particularly useful for coffee AFS discrimination. However, supplementary data are required to improve the performance of the classifier. Our findings also highlight the importance of the multi-temporal and multi-dataset approach for identifying complex production systems in areas of high topographic heterogeneity.

Keywords: Sierra Madre; Chiapas; Random Forest; Shade coffee; Recursive Feature Elimination

1. Introduction

Coffee is one of the most important agroforestry crops in Latin America; 80% of the global production of Arabic coffee is grown in this region [1]. Given its importance, this crop has significantly modified the structure of rural landscapes in coffee-growing regions [2]. About 25 million rural farmers depend on coffee-growing for their livelihoods; most of them are small farmers with crops ranging from 1 to 5 ha [3].

In Mexico, coffee is cultivated mainly in agroforestry systems (AFS), also known as shade coffee [4]. In AFS, coffee plants grow understory under the canopy of native or introduced tree species [5]. Shade trees, which can be either timber or fruit trees, regulate light conditions for optimal coffee-growing, capture carbon, control soil erosion, and provide shelter for biodiversity [6]. Additionally, these trees are a source of firewood, food, and additional economic income for farmers [7,8]. Coffee agroforestry systems are found in a wide variety of socio-environmental contexts with different anthropic alteration level, densities and compositions of shade trees and involving several varieties of coffee plants adapted to various geographic regions [9]. These modifications have also been aimed at reducing the incidence of pests and diseases [10].

Coffee AFS can be characterized by a combination of attributes, such as the density of shade trees, the abundance of non-native species and the use of agrochemicals, which can be used to describe the levels of anthropogenic crop disturbance. In this regard, Toledo and Moguel [11] elaborated a proposal for a disturbance gradient with four classes. According to their proposal, the AFS with the lowest disturbance level, "rustic systems", are those where coffee cultivation is introduced into the mature native forest, either replacing or supplementing the vegetation in the understory. In contrast, the system with the higher levels of anthropic impact, or "shade monocultures", are those where coffee plants are established under trees of a single species and often require the application of agrochemicals; these systems provide less environmental services [12]. Finally, these authors also included a fifth, the highest disturbance class, corresponding to coffee crops without shade trees (i.e., not an AFS), also known as sun coffee. In Mexico, coffee production is concentrated in four states: Chiapas, Veracruz, Oaxaca, and Puebla. The first covers 35% of the total area cultivated in Mexico, or approximately 252,000 ha, with 90% involving some type of AFS [4,13]. However, the incidence of pests and diseases, particularly the coffee rust (*Hemileia vastatrix*), has forced many farmers to replace their old coffee varieties with more resistant ones that require fewer shade trees, thus increasing the anthropization of coffee-growing systems [14].

Despite the importance of shade coffee production in Chiapas, the detailed spatial distribution of the different types of coffee agroforestry systems is still unknown. This lack of information is caused by the poor accessibility to coffee plantations since a significant number of coffee grower farmers are in highly marginalized areas, with small coffee plots areas (about one hectare) scattered in hard-to-access mountain landscapes [15].

Mapping the area covered by coffee AFSs using remote sensors has been unsuccessful, particularly regarding systems with high density of shade trees, which have been identified with low accuracy [16,17]. Topographic heterogeneity, ASF structural complexity, and shade tree coverage are some of the factors that restrain correct identification of these AFS. As a result of the complexity of coffee-growing landscapes, their spectral patterns are often misidentified by other types of land cover, such as forests and secondary vegetation [17,18].

In the case of sun coffee plantations, which have few shade trees, if any, land cover classification has been performed well. Accuracy values above 90% have been reported in plantations with reduced vegetation cover, by combining spectral bands and vegetation indices from optical images [19] and including texture metrics as predictive variables [20]. In situations of intermediate complexity, using high-resolution images in areas with homogeneous topography, Hebbar et al. [21] identified commercial poly- and monocultures with a low error. In more complex AFSs, the use of supplementary information, including slope, temperature, precipitation, and soil fertility, improved the accuracy of crop identification [22]. Separately, Kelley et al. [23] used spectral indices and land surface temperature derived from multi-seasonal Landsat 8 imagery to detect coffee AFS with a percentage of shade trees above 30%.

On the other hand, the modification of AFS spectral patterns associated with phenological changes has been little explored. Few studies have attempted to discriminate the types of AFS using temporal variations of their spectral response [23–26]. Considering the importance of the shade coffee plantations for Chiapas México and the difficulties in identifying them, the aim of this study was twofold. First, we seek to develop a method for the identification of coffee AFS types with different densities of shade trees, using variations in spectral response throughout the dry season as well as spectral indices and auxiliary data. We also expected to improve the accuracy of land cover maps of coffee of agroforestry systems of Chiapas using this approach.

2. Materials and Methods

2.1. Study Area

The study area stretches across 2381 km^2 and is located in the central part of the mountain range called Sierra Madre de Chiapas (Figure 1). This region harbors a high biodiversity and has the highest coffee production in the state of Chiapas [27]. The study area was limited to potential coffee growing areas, i.e., those between 700 and 2800 meters above sea level using a Digital Elevation Model downloaded from the Digital Library of Maps of the National Institute of Statistics, Geography, and Informatics [28].

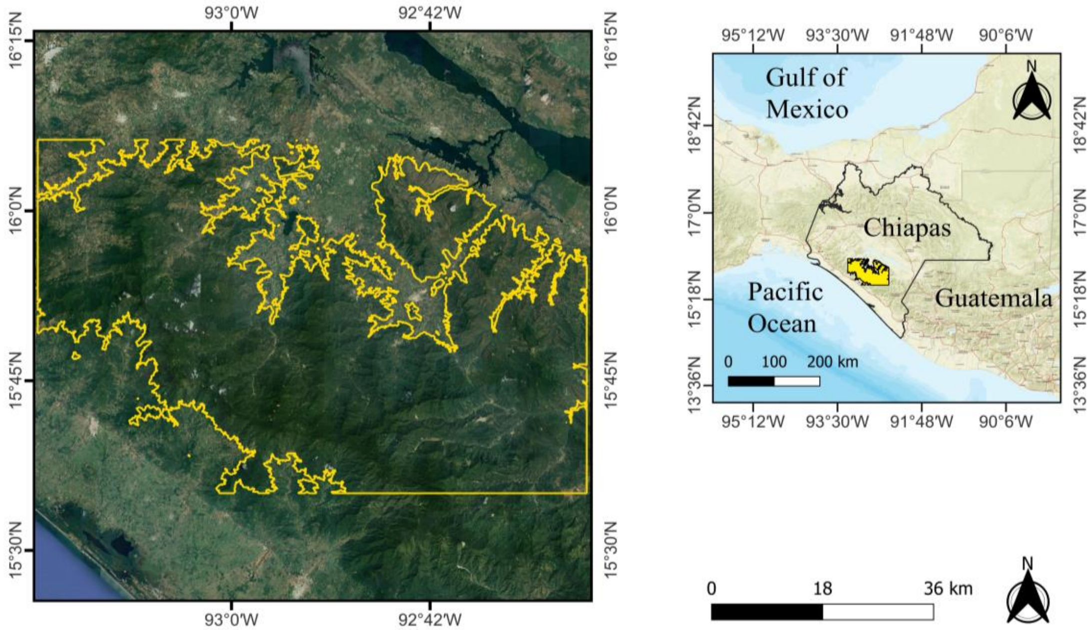


Figure 1. Location of the study area. Source: World Imagery, ESRI, Copyright: © 2022 Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

Due to its mountainous relief, the area covers a wide altitudinal gradient, from 700 to 2700 meters above sea level. In the dry season, the minimum temperate fluctuates between 9 and 15 °C and the maximum temperature between 21 and 33 °C, with precipitation between 25 and 300 mm [29]. The region encompasses a significant diversity of forest types, including coniferous forest, mountain cloud forest, tropical dry forest and tropical wet forest. In some cases, these show degradation and fragmentation of forest cover as a result of illegal logging, livestock ranching, and rainfed agriculture. As a result, fragments of secondary forests in different successional stages are also common [30].

2.2. Field Data and Characterization of Agroforestry Systems

The characterization of coffee AFS types and the calibration of the models were conducted using an inventory of 263 shade coffee plots collected in 2019 by the Café de La Concordia (CAFECO, for its acronym in Spanish) cooperative organization of coffee growers. In each plot, CAFECO recorded information on coffee and the geographic coordinates of the plot center, the number and varieties of coffee plants, and the number and botanical names of the shade trees. Besides, we collected similar data in additional 15 plots; we also registered mean height, mean diameter at the breast height, crown diameter and the number of strata of the coffee plants and shade trees.

According to an analysis of field data (abundance and species composition of shade trees, and density of coffee plants) and a visual interpretation of satellite images, we generated a dataset of 150 field plots and grouped into three classes of AFS (Figure 2). The definition of these classes partially matches that proposed by Moguel and Toledo [31], adapted to the characteristics of the local production systems in the study area. The definitions of coffee AFS types used in this study are the following:

1. *Reduced-shade coffee polyculture*. This system has one or two tree strata and an understory layer with coffee plants. The highest stratum shows some trees of natural vegetation, usually the tallest trees (>7 m). When there is an intermediate stratum, it usually includes fruit and timber tree species; the most common species are *naranja* (*Citrus × sinensis (L.) Osb.*), *aguacate* (*Persea americana Mill.*), *plátano* (*Musa paradisiaca L.*), *zapote* (*Pouteria sapota (Jacq.) H.E. Moore & Stearn*), and *mango* (*Mangifera indica L.*). The percentage shade is generally less than or equal to 30%, the tree density varies from 16 to 30 trees per hectare, and the density of coffee plants ranges from 2500 to 4400 plants per hectare. Although trees are not evenly distributed, the distance between shade trees is usually wide, so there are open areas and coffee plants are frequently apparent in high-resolution images (Figure 2b).
2. *Rustic coffee polyculture*. This AFS has two tree strata and an understory of coffee plants. The highest stratum includes trees of natural vegetation, in some cases alternating with introduced timber trees, mainly *cedro* (*Cedrela odorata L*.) and *roble* (*Quercus robur L*.); the average height of this stratum is 10 m. The second stratum generally comprises introduced species with a mean height of 6 m, commonly *chalum* (*Inga vera Willd*.), *caspirol* (*Inga laurina (Sw.) Willd*.), *paterna* (*Inga spuria H & B. Ex Willd*.), and fruit trees such as *naranja* (*Citrus × sinensis (L.) Osb*.), among others. The percentage of shade ranges from 30% to 60%. The density of shade trees varies between 24 and 38 trees/ha; the density of coffee plants, between 2500 and 4800 plants/ha. In satellite images, these systems

appear more homogeneous in color compared to forests and tropical forests and are less fragmented (Figure 2c) and less intensely colored than reduced-shade polycultures.

3. *Rustic coffee*. This system also has one or two strata of tree vegetation; the highest stratum is dominated by species of natural vegetation, with occasional introduced trees. The intermediate stratum consists mainly of timber trees, including *chalum* (*Inga vera Willd*.), *caspirol* (*Inga laurina (Sw.) Willd.*) and *paterna* (*Inga spuria H & B. Ex Willd*.) of lower height.

   The percentage of shade is greater than 60%. Compared to the other AFS classes, this class has a higher density of shade trees (30–44 trees/ha), with a similar density of coffee plants (2500–3300 plants/ha). This system is the one leading to greater spectral confusion with forests and tropical forests because the three show similar tonalities and texture patterns (Figure 2d).

The study area has no sun coffee plantations but includes other types of land cover such as mature forests, disturbed forests, shrub and herbaceous secondary vegetation, human settlements, pastures, oil palm (*Elaeis guineensis Jacq*.), mango plantations and bare soil. These land-covers were classified into three groups. The final classes used for a land cover map with coffee plantations are shown in Table 1. The sixth group, *other classes*, includes human settlements, agriculture, and bare soil.

Table 1. AFS and landcover classes in the study area.

ID	**Classes**
1	Reduced-shade coffee polyculture
2	Rustic coffee polyculture
3	Rustic coffee
4	Mature forests
5	Disturbed forests
6	Other classes

Figure 2. Coffee agroforestry systems defined for the study area. a) Sample polygons of each type of coffee agroforestry system, b) reduced-shade coffee polyculture, c) rustic coffee polyculture, d) rustic coffee.

2.3. Imagery and auxiliary data

To reduce the presence of clouds and haze, we selected optical satellite imagery from January to May 2019 only, corresponding to the dry season. We used a monthly time series of five Sentinel-2 images (Level 1C); two Sentinel-2 scenes covered the whole study area. We also analyzed five Sentinel-1 (Interferometric Wide Swath Level 1) radar images with VV and VH polarization acquired on similar dates as the optical data and one Alos Palsar with HH and HV polarization from the JAXA Earth Observation Research Center (https://www.eorc.jaxa.jp). Satellite imageries were downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/). The auxiliary data employed consists of a Digital Elevation Model (DEM) and a climatic data set. A 30 m pixel size DEM was downloaded from the Digital Library of Maps of the National Institute of Statistics, Geography and Informatics (Instituto Nacional de Estadística, Geografía e Informática) [28]. We used the following climatic data: monthly temperature (minimum and maximum), monthly precipitation and soil moisture; these variables were interpolated from meteorological data and prepared in raster layers with a pixel size of 120 m (for further details, refer to Hernández-Stefanoni et al. [32]).

2.4. Image processing

Using the software SNAP [33], atmospheric corrections were applied to all optical 172 images to reduce the potential effect of water vapor and obtain bottom of atmosphere (BOA) reflectance values. Bands were resampled using the Sen2Res algorithm to match the pixel size to 10 m.

To highlight any changes in the spectral response of AFS during the dry season, the following six vegetation indices were calculated for each of the five months analyzed. The Chlorophyll Vegetation Index (CVI) and Modified Simple Ratio for Vegetation (MSR) highlight information associated with chlorophyll content [34]. The combination of the Modified Chlorophyll Absorption in Reflection Index (MCARI) and the Optimized Soil Adjusted Vegetation Index (OSAVI) reduce background reflectance and improve sensitivity to variability in leaf chlorophyll content [35]; this combination is especially useful for reducing the reflectance of non-photosynthetic components and soil [34]. In addition, we calculated the Beison Datt Vegetation Index (DATT), the RGB Intensity, and the Soil

Background Line (SBL) to evaluate more efficient alternatives for estimating canopy attributes and color saturation in RGB composites, and to discriminate between soil and vegetation cover (table 2).

We preprocessed the Sentinel-1 images using the standard generic workflow available in SNAP. This workflow applies precise orbit of acquisition, removes thermal and edge noise, and performs radiometric calibration and geometric terrain correction [36]. The layers used are shown in Table 3.

Table 2. Equations of the vegetation indices used in this study. Ri = Reflectance in range i.

Vegetation Index	Equation		Reference
CVI	$R_{842}\frac{R_{665}}{{R_{560}}^2}$	(1)	[37]
MSR	$\frac{R_{800}-R_{445}}{R_{680}-R_{445}}$	(2)	[38]
MCARI/OSAVI	$\frac{[(R_{700}-R_{670})-0.2(R_{700}-R_{550})](\frac{R_{700}}{R_{670}})}{(1+0.16)\frac{(R_{800}-R_{670}}{R_{800}+R_{670}+0.16}}$	(3)	[35]
DATT	$\frac{R_{850}}{R_{550}\times R_{708}}$	(4)	[38]
RGB Intensity	$(\frac{1}{30.5})(R_{0.490}+R_{0.560}+R_{0.665})$	(5)	[39]
SBL	$R_{945}-2.4\times R_{0.665}$	(6)	[40]

Table 3. Data used for the identification of coffee agroforestry systems.

Data type	Sources	Date	Input variables
Optical	Sentinel-2 (Dry Season)	01/23/2019 02/20/2019 03/24/2019 04/23/2019 05/24/2019	Reflectance bands: Band 2 - Blue Band 3 - Green Band 4 - Red Band 5 – Red-edge Band 7 – red-edge Band 8 - NIR Band 8A – Red-edge Band 9 - Water vapour Band 11 – SWIR Vegetation indices: CVI MSR MCARI/OSAVI DATT SBL RGB Intensity
Auxiliary data	DEM		Altitude
	Climatic data		Mean monthly soil wetness (January, February, March, April, May) Mean monthly temperature (January, February, March, April, May) Mean monthly precipitation (January, February, March, April, May)
Radar	Sentinel-1A (Dry Season)	02/12/2019 03/24/2019 05/08/2019	Beam mode: IW Polarization: VV+VH Band: C-Band Spatial resolution: 20m Ascending
	Sentinel-1B (Dry Season)	01/25/2019 04/23/2019	Beam mode: IW Polarization: VV+VH Band: C-Band Spatial resolution: 20m Ascending
	Alos PALSAR (Dry Season)	2019	Beam mode: FBD Polarization: HH+HV Band: L-Band Spatial resolution: 25m

2.5. Data analysis and land cover classification

To aim in the selection of explanatory variables, we plotted the monthly values of vegetation indices and spectral bands for each type of AFS. This preliminary analysis revealed that some AFS showed changes in spectral patterns in certain months, i.e., bigger separability between index values/spectral bands, so we tried to keep these variables/months in the following stages. Then, a correlation analysis was performed with all possible explanatory variables, including spectral bands, vegetation indices and auxiliary data; the Spearman index was used to detect possible cases of non-linear correlation. At this stage, all highly correlated variables were eliminated, i.e., those with a Spearman index greater than 0.85.

With the resulted set of predictor variables, four subsets were constructed — one for each AFS type and one for the rest of land-cover types in the study area. The Recursive Feature Elimination (RFE) algorithm was used to select the best subset of predictors for each model [41] under the criterion of mean decrease in accuracy (MDA). The MDA was calculated through random permutation of the input variables, and the decrease in the accuracy of the resulting prediction was assessed [42]. Each model included direct information (optical image reflectance), derived information (vegetation indices), and supplementary data (soil moisture and altitude) according to their relevance for the identification of cover classes. The parameters of the best sets of predictive variables defined for each model were adjusted using the Random Forest algorithm. Through the cross-validation of ten interactions, the *ntree* (number of trees to grow) and *mtry* (number of variables randomly sampled as candidates in each division) parameters were chosen for the selection of the best classification model.

Once the models were calibrated, the four respective classifications were obtained, which were spatially overlaid to identify conflicting pixels, i.e., those assigned to more than one type of AFS or land cover class. The class to which each conflicting pixel should belong was assigned using the maximum likelihood algorithm; Sentinel-2 scenes and the training areas previously were used as input data. The resulting classifications were combined to generate a single land cover map with the different types of AFS identified. The overall methodological outline is shown in Figure 3.

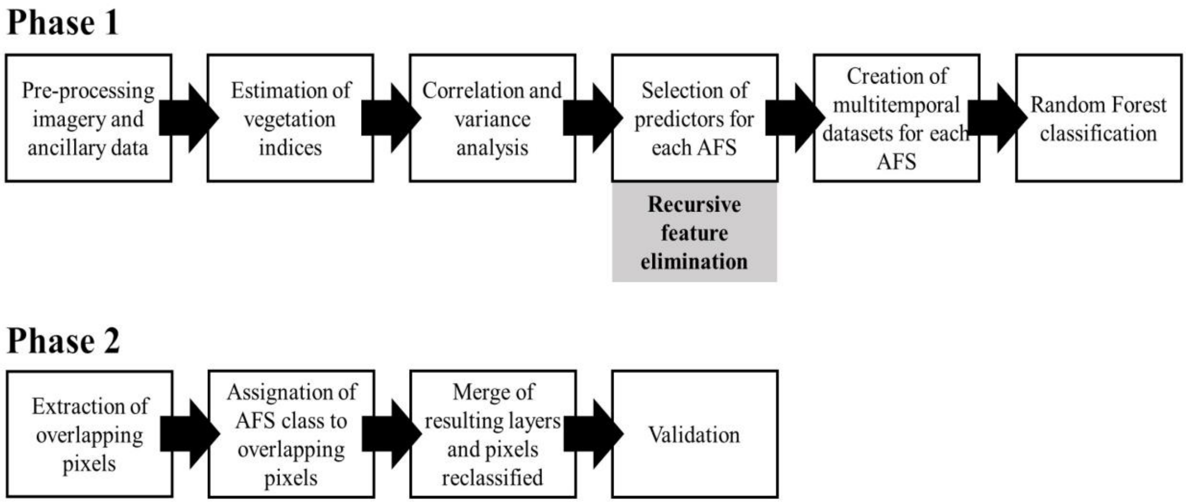


Figure 3. Methodology for the identification of AFS classes.

2.6. Map validation

We followed the recommendations of Oloffson et al. [43] to validate the final map. A stratified random sampling design was used to estimate the size and distribution of the reference sample. The number of validation sites in each landcover class was allocated proportionally to their size; small classes were assigned at least 50 sites. Thematic accuracy statistics were derived according to the equations described in Oloffson et al. [44]. The ground truth of the reference data was obtained by photo interpretation of high spatial resolution imagery; Planet image mosaics (4.7 m pixel size) downloaded from the NICFI Satellite Data Program (https://www.planet.com/nicfi/) and satellite data available from ESRI's World Imagery platform [45] via the Qgis software [46] were used. In the latter platform, although it has very high spatial resolution data, it is not possible to know their characteristics; however, according to the available documentation, at least 2.5 m SPOT images can be found in most of the world.

3. Results

3.1. Selecting Predictors and Applying the Classification Model

The subsets defined for each model from the implementation of the RFE algorithm are shown in Table 4. The two January NIR bands functioned well as predictive variables for the three AFS types but played no significant role in the model for other land-cover types.

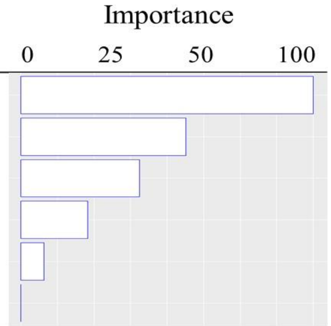
Green and red edge bands are important for the two AFS with the highest tree density, but their role is taken up by the SWIR band in the model with the lowest tree density (reduced-shade polyculture). In all models, only the first four or five variables have high predictive importance. However, eliminating any variable with low importance in the models increases the error in the resulting classified map. The importance level of each predictor estimated through the mean decrease in accuracy is shown in Figure 4. Note that none of the models contains variables derived from radar imagery.

Table 4. Predictors selected for each classification process. NIR = Near infrared, SWIR = Short-wave infrared, Bi = band i.

Class	**Predictors selected using RFE**
Reduced-shade coffee polyculture	NIR B8 (January), NIR B8A (January), SWIR B11 (April, May), CVI (January), MSR (January)
Rustic coffee polyculture	Red edge B7 (January), NIR B8 (January), NIR B8A (January), Green B3 (January), MCARI/OSAVI (January), Soil humidity (January)
Rustic coffee	Red edge B7 (January), NIR B8 (January), NIR B8A (January), Green B3 (January), Red edge B5 (January), RGB Intensity (January)
Mature forests, disturbed forests and other classes	Blue B2 (January, February, March), SWIR B11 (May), RGB Intensity (February), DATT (January), SBL (January)

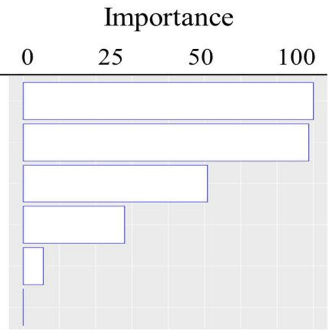
Predictors for reduced-shade coffee polyculture

Predictor	Mean influence	SD influence
1 CVI	15.00	6.69
2 SWIR B11 (April)	6.07	0.62
3 SWIR B11 (May)	5.31	0.68
4 NIR B8A (January)	4.50	0.49
5 MSR	4.21	0.99
6 NIR B8 (January)	3.38	0.84



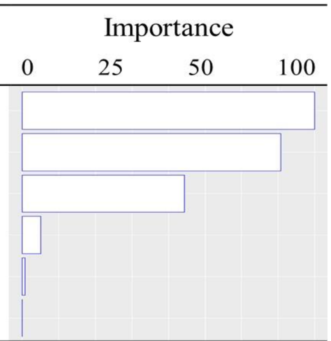
Predictors for coffee polyculture

Predictor	Mean influence	SD influence
1 Soil humidity (March)	24.80	5.00
2 MCARI/OSAVI	11.90	3.05
3 NIR B8A (January)	7.72	3.12
4 Green B3 (January)	7.56	0.65
5 NIR B8 (January)	5.20	1.42
6 Red egde B7 (January)	3.85	0.76



Predictors for rustic coffee

Predictor	Mean influence	SD influence
1 Green B3 (January)	18.30	4.52
2 RGB Intensity	9.73	2.00
3 NIR B8A (January)	8.67	3.91
4 NIR B8 (January)	8.59	1.12
5 Red egde B5 (January)	8.37	1.88
6 Red egde B7 (January)	4.20	0.57



Predictors for mature forests, disturbed forests, and other classes

Predictor	Mean influence	SD influence
1 SWIR B11 (May)	35.40	9.30
2 RGB Intensity	34.20	5.46
3 DATT	16.20	4.78
4 Blue B2 (January)	6.27	0.72
5 Blue B2 (March)	6.16	1.39
6 Blue B2 (February)	6.02	1.82

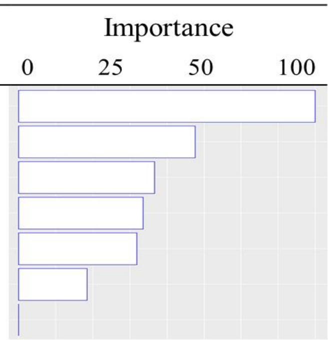


Figure 4. Predictors and their influence for each class in the RF classification. SD = Standard deviation.

The optimal parameters for the Random Forest classification models (*mty* = 3 and *ntree* = 500) achieved accuracy values above 98% for the three AFS models and above 99% for the other land-cover classes.

The individual maps for reduced-shade polycultures, rustic polycultures, rustic coffee, and other classes are shown in Figure 5.

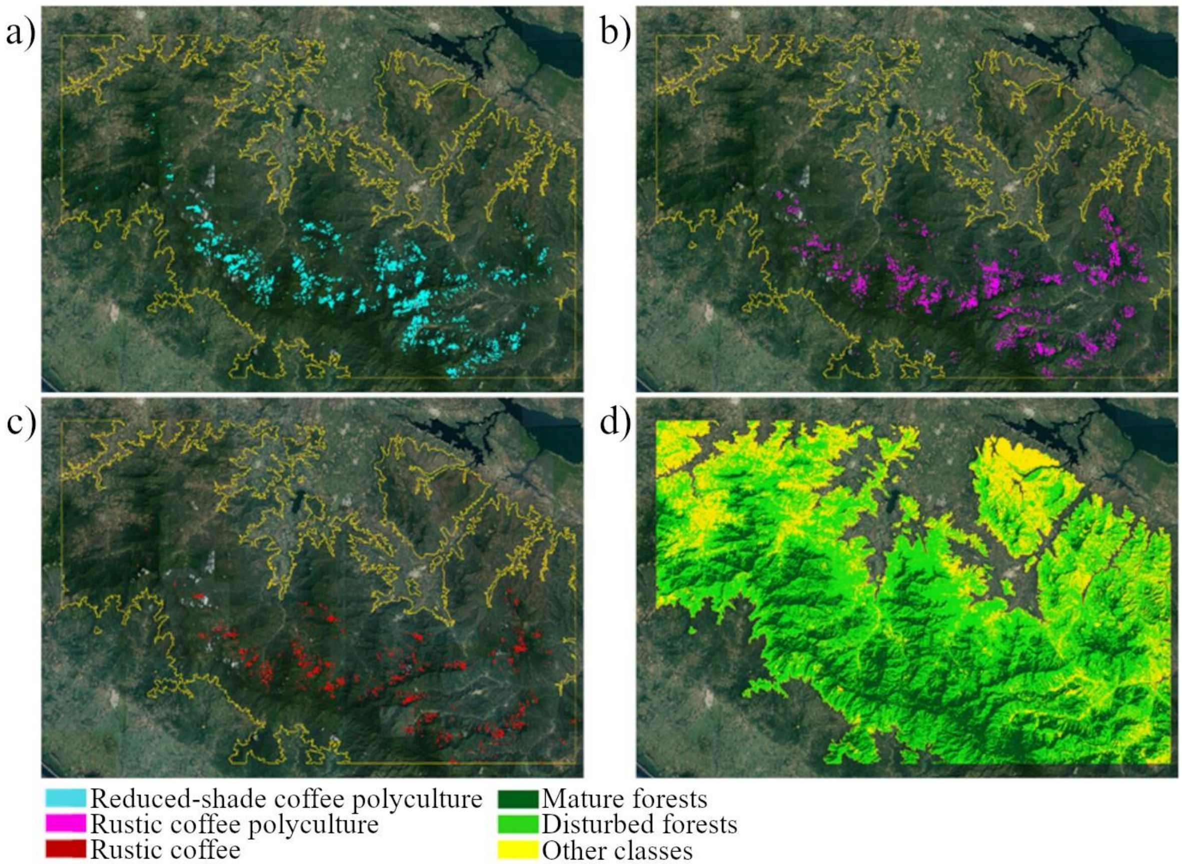


Figure 5. Individual maps for a) reduced-shade coffee polyculture, b) rustic coffee polyculture, c) rustic coffee, and d) mature forest, disturbed forest and other classes.

The conflicting pixels identified from class overlaying accounted for 0.71% of the total study area. The disturbed forest was the class that showed the greatest misidentification with other classes, mainly with rustic polycultures and rustic coffee.

Reduced-shade polycultures shade was frequently located in areas adjacent to human settlements and areas with agricultural or livestock activities, between 700 and 1500 meters above sea level. Rustic polycultures and introduced coffee were identified mainly in disturbed forests areas near mature forests and tropical forests at altitudes above 1400 m.a.s. l. However, rustic coffee plantations were located near disturbed forests with a higher tree density. Of total area identified as an agroforestry coffee system, reduced-shade polycultures were the systems comprising the largest area (40%) while rustic coffee plantations encompassed the smallest area (23%); the extent occupied by AFS was considerably smaller compared with mature and disturbed forests.

The information in the infrared range of the electromagnetic spectrum contributed significantly to differentiation between disturbed forest and coffee AFS because the coffee flowering phase of the phenological cycle produces an apparent change in the red edge and SWIR bands in the spectral signature of coffee AFS (Figure 6).

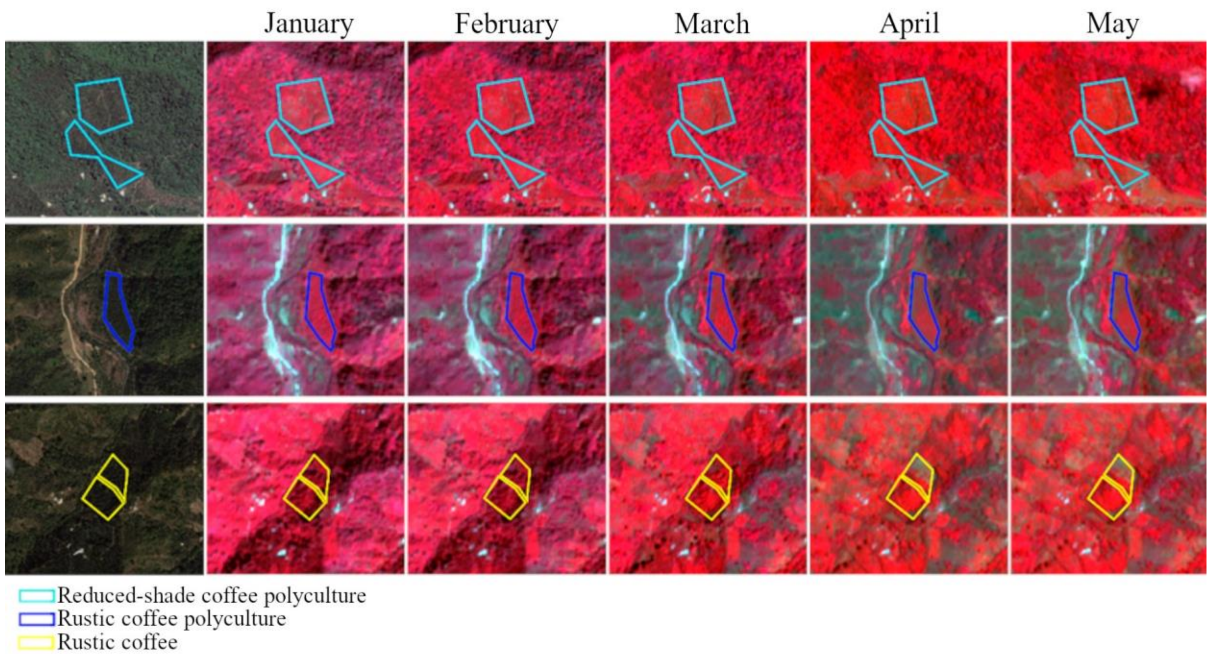


Figure 6. Spectral profile variations for coffee agroforestry systems in Color Infrared (B8, B4, B3) from Sentinel-2.

3.2. Model validation

The map resulting from the overlay of individual classifications is shown in Figure 7. Table 5 shows the confusion matrix obtained from the reference sample, and Table 6 shows their respective accuracy statistics. The global accuracy of the map was 94.5%. The AFS identified with less error are the reduced-shade coffee polyculture and rustic coffee polycultures, which involve a more significant anthropic influence within the proposed AFS classification. Reduced-shade coffee polycultures showed only one instance of a validation site misclassified as disturbed forest. Rustic coffee polycultures are misclassified either as reduced-shade coffee polyculture or rustic coffee, mainly at sites that transition from one AFS to another, whereas rustic coffee class was confused a couple of times with disturbed forest and rustic coffee polyculture. Two of the three AFS were well identified, with high accuracy (>92%), but the third, rustic coffee, was the class with the most significant error. This error is mainly due to their spectral similarity with disturbed forests.

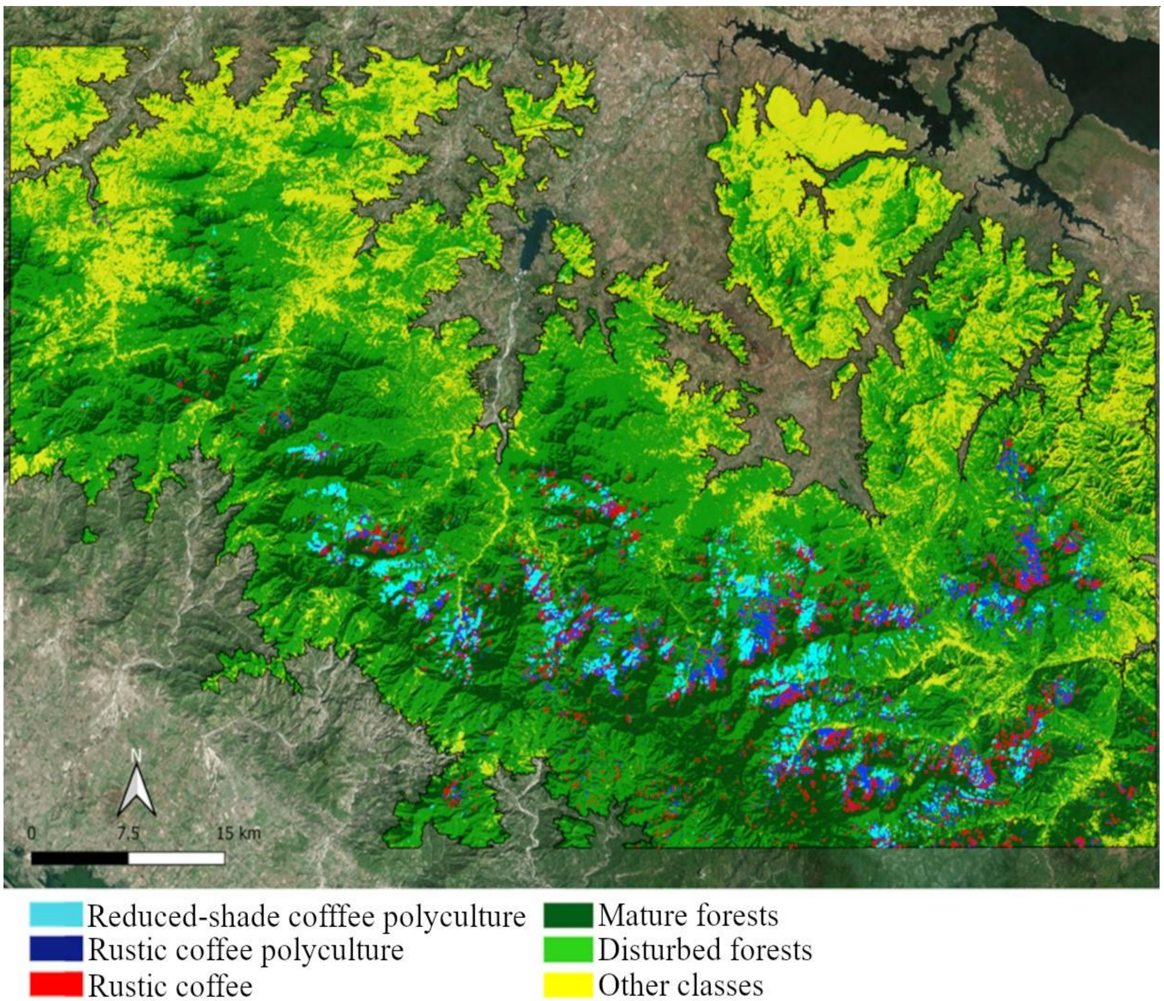


Figure 7. Final map after to overlap all models' classifications.

Table 5. Confusion matrix generated using 932 validation sites.

Reference Prediction	Reduced shade coffee poly-culture	Rustic coffee poly-culture	Rustic coffee	Mature forest	Disturbed forest	Other classes	Total
Reduced-shade coffee polyculture	48	2	0	0	2	0	**52**
Rustic coffee polyculture	2	47	2	0	0	0	**51**
Rustic coffee	0	1	46	0	2	0	**49**
Mature forest	0	0	0	50	2	0	**53**
Disturbed forest	0	0	2	1	525	7	**535**
Other classes	0	0	0	0	29	164	**193**
Total	**50**	**50**	**50**	**51**	**560**	**171**	**932**

Table 6. Accuracy statistics, where CI = confidence interval, PA = producer accuracy, UA = user accuracy, OA = Overall accuracy, ± = variance.

	Area per class(km^2)	Area estimated per class(km^2)	CI of estimated area (km^2±)	PA (%)	UA (%)	OA (%)
Reduced-shade coffee polyculture	26.82	26.47	3.06	93.55	92.31	95.04
Rustic coffee polyculture	43.56	42.09	3.96	95.39	92.16	
Rustic coffee	44.56	52.03	12.37	80.39	93.88	
Mature forest	208.80	205.02	13.81	97.93	96.15	
Disturbed forest	2271.90	2344.68	45.20	95.08	98.13	
Other classes	694.56	619.93	41.38	95.20	84.97	

4. Discussion

To improve the accuracy of coffee agroforestry maps we used a strategy of adjusting separate models for each AFS type allowed using a small and specific number of predictor variables for each land cover class, without affecting their performance. The resulting map showed a global accuracy of 95.4%. The incorporation of different vegetation indices for each AFS type increased the accuracy of each model, in other words, the use of different sets of predictor variables was more efficient in discriminating agroforestry systems with different shade densities. Although a potential disadvantage of this approach is the presence of conflicting pixels, particularly in land-cover classes that were not clearly differentiated spectrally, in the present study, those pixels represented only 0.7% of the study area and mostly corresponded to AFSs with high tree density and disturbed forests.

In addition, although some variables were repeated in several models, the explanatory importance of each varied across the four models. Vegetation indices were key for discriminating AFS with lower tree density; high values of the CVI and MSR vegetation indices in the coffee flowering phases contrasted with the response of the disturbed forest. On the other hand, topographic or climatic data did not play a significant role in the models (except for one), probably due to their low spatial resolution.

Although it is difficult to compare the level of success of this work with that of other studies (due to the diversity of AFS types, landscape complexity or data sources), broadly speaking, the accuracies obtained in this study are moderately higher than those reported under similar conditions. In highly heterogeneous landscapes, the present study improved the accuracy of open-canopy coffee AFS (canopy opening greater than 60 %) and closed-canopy coffee AFS (canopy opening between 20 to 60 %) identification by approximately 30% [22,25,47]. Compared with studies using radar images, this research achieved greater accuracy in identifying reduced-shade polycultures versus AFS with similar characteristics, such as commercial polycultures or coffee plantations with a low tree coverage [48]. Our methodological approach also was efficient for differentiating AFSs within forest landscapes, reported as a common issue when using conventional satellite images [49,50].

It should be noted that in the present study, in addition to optical images, we also tested Sentinel-1 and an ALOS-PALSAR images. However, the REF algorithm consistently eliminated them from the set of predictive variables since they provided little information. The topographic complexity of the study area appeared to be an obstacle for the use of radar data.

Usually, the flowering of coffee plants occurs at the end of the dry season [51]; this phenomenon causes changes in the concentrations of chlorophyll *a* and *b* and the leaf area index [52,53]. These phenological changes represent the leading cause of changes in spectral patterns in coffee-growing areas, consistent with the results of the studies by Bernardes et al. [51] and Júnior et al. [54], that addressed the relationship of coffee production at different stages of the cycle and the variation in vegetation indices over several years. Regarding our results, one model uses spectral data from the beginning and the end of the study period (January and April-May), this model corresponds to the AFS with few shade trees, so it is probably the one that is capturing the phenological changes of the coffee plants.

Accurate mapping of coffee agroforestry systems is essential for understanding the level of anthropic disturbance and change in plant cover of coffee production areas. According to our results, at least 50% of the AFS areas are heavily anthropized. This finding is consistent with the trends in other studies that reported changes in management practices to fight coffee rust, which generally involved replacing coffee varieties and reducing shade-tree density [55].

5. Conclusions

This study used a differentiated analysis approach by type of AFS to map coffee production in areas of high heterogeneity. The results reported herein are significant given the limitations highlighted in previous studies of the conventional use of remote sensing data for mapping coffee agroforestry systems and the accuracy levels reported for similar implementation contexts. The accurate identification of AFS contributes to the knowledge of the anthropic disturbance dynamics associated with coffee production by highlighting three different levels of landscape alteration for agroforestry practices. In this sense, subsequent studies may use this same approach in other coffee-growing areas in the state of Chiapas to explore the existence of systems with different characteristics than the AFS described herein and to evaluate the replicability of the method under different landscape characteristics. On the other hand, future studies may use specific subsets for other types of plant cover or land use such as mature and disturbed forests to further improve the accuracy of the resulting classification.

Author Contributions: Conceptualization: M.A. C-S, A. E-L; methodology: A. E-L, M.A. C-S; software: A. E-L; validation: M.A. C-S, A. E-L, J.L. H-S, J.F. M, J.O. L-M; formal analysis: A. E-L; investigation: A. E-L, M.A. C-S; Resources: M.A. C-S, A. E-L, J.L. H-S, J.F. M, J.O. L-M; writing-original draft preparation: A. E-L; writing-review and editing: M.A.

C-S, J.L. H-S, J.F. M, J.O. L-M; supervision: M.A. C-S. All authors have read and agreed to the published version of the manuscript.

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6. References

1. ITC. The Coffee Guide. Technical report, The International Trade Centre (ITC), Geneva, Switzerland, 2021.
2. Perfecto, I.; Jiménez-Soto, M.E.; Vandermeer, J. Coffee Landscapes Shaping the Anthropocene. Current Anthropology 2019, 60, S236–S250. https://doi.org/10.1086/703413.
3. Harvey, C.A.; Martínez-Rodríguez, M.R.; Cárdenas’, J.M.; Avelino, J.; Rapidel, B.; Vignola, R.; Donatti, C.I.; Vilchez-Mendoza, S. The Use of Ecosystem-based

Adaptation Practices by Smallholder Farmers in Central America. Agriculture, Ecosystems & Environment 2017, 246, 279–290. https://doi.org/10.1016/j.agee.2017.04.018.

4. CEDRSSA. Reporte del café en México: Diagnóstico y perspectiva. Technical report, Cámara de Diputados, Ciudad de México, 2018. Publication Title: Reporte del café en México: diagnóstico y perspectiva.
5. Farfán-Valencia, F. Descripción de la Estructura del Dosel Arbóreo al Interior de un Sistema Agroforestal con Café. Technical report, Centro Nacional de Investigaciones de Café, Manizales, Caldas, Colombia, 2019.
6. Jose, S. Environmental Impacts and Benefits of Agroforestry. In Oxford Research Encyclopedia of Environmental Science; Oxford University Press, 2019. https://doi.org/10.1093/acrefore/9780199389414.013.195.
7. Ospina, C. Climate and Economic Benefits of Agroforestry Systems. Climate Institute 2017, p. 11. Place: Washington, DC.
8. DaMatta, F.; Nelson, R. Sustainable Production of Coffee In Agroforestry Systems in the Neotropics: An Agronomic and Ecophysiological Approach. Agronomía Colombiana 2007, 1, 113–123.
9. Montagnini, F.; Somarriba, E.; Murgueitio, E.; Fassola, H.; Eibl, B. Función de los sistemas agroforestales en la adaptación y mitigación del cambio climático. In Sistemas agroforestales. Funciones productivas, socioeconómicas y ambientales; CATIE: Turrialba, Costa Rica, 2015; pp. 269–298.
10. Harvey, C.A.; Pritts, A.A.; Zwetsloot, M.J.; Jansen, K.; Pulleman, M.M.; Armbrecht, I.; Avelino, J.; Barrera, J.F.; Bunn, C.; García, J.H.; et al. Transformation of Coffee-growing Landscapes Across Latin America. A Review. Agronomy for Sustainable Development 2021, 41, 62. https://doi.org/10.1007/s13593-021-00712-0.
11. Toledo, V.M.; Moguel, P. Coffee and Sustainability: The Multiple Values of Traditional Shaded Coffee. Journal of Sustainable Agriculture 2012, 36, 353–377. https://doi.org/10.1080/10440046.2011.583719.
12. Jha, S.; Bacon, C.M.; Philpott, S.M.; Rice, R.A.; Méndez, V.E.; Läderach, P. A Review of Ecosystem Services, Farmer Livelihoods, and Value Chains in Shade Coffee Agroecosystems; 2011; pp. 141–208. https://doi.org/10.1007/978-94-007-1309-3_4.

13. INCAFECH. Datos importantes del café, 2018.
14. Valencia, V.; García-Barrios, L.; Sterling, E.J.; West, P.; Meza-Jiménez, A.; Naeem, S. Smallholder response to environmental change: Impacts of coffee leaf rust in a forest frontier in Mexico. Land Use Policy 2018, 79, 463–474. https://doi.org/10.1016/j.landusepol.2018.08.020.
15. Higuera-Ciapara, I.; Rivera-Ramírez, J. Chiapas: Problemáticas del Sector Cafetalero; Centro de Investigación y Asistencia en Tecnología y Diseño del Estado de Jalisco: Guadalajara, 2018. Publication Title: Centro de Investigación y Asistencia en Tecnología y Diseño del Estado de Jalisco.
16. Boell, M.; Ramos Alves, H.; Volpato, M.; Ferreira, D.; Lacerda, W. Exploiting Feature Extraction Techniques for Remote Sensing Image Classification. IEEE Latin America Transactions 2018, 16, 2657–2664. https://doi.org/10.1109/TLA.2018.8795147.
17. Hunt, D.A.; Tabor, K.; Hewson, J.H.; Wood, M.A.; Reymondin, L.; Koenig, K.; Schmitt-Harsh, M.; Follett, F. Review of Remote Sensing Methods to Map Coffee Production Systems. Remote Sensing 2020, 12, 2041. https://doi.org/10.3390/rs12122041.
18. Souza, C.G.; Carvalho, L.; Aguiar, P.; Arantes, T.B. Algoritmos de Aprendizagem de Máquina e Variáveis de Sensoramento Remoto para o Mapamento da Cafeicultura. Boletim de Ciências Geodésicas 2016, 22, 751–773. https://doi.org/10.1590/s1982-21702016000400043.
19. Schmitt-Harsh, M.; Sweeney, S.P.; Evans, T.P. Classification of Coffee-Forest Landscapes Using Landsat TM Imagery and Spectral Mixture Analysis. Photogrammetric Engineering & Remote Sensing 2013, 79, 457–468. https://doi.org/10.14358/PERS.79.5.457.
20. Mosomtai, G.; Odindi, J.; Abdel-Rahman, E.M.; Babin, R.; Fabrice, P.; Mutanga, O.; Tonnang, H.E.Z.; David, G.; Landmann, T. Landscape Fragmentation in Coffee Agroecological Subzones in Central Kenya: A Multiscale Remote Sensing Approach. Journal of Applied Remote Sensing 2020, 14. https://doi.org/10.1117/1.JRS.14.044513.
21. Hebbar, R.; Ravishankar, H.M.; Trivedi, S.; Manjula, V.B.; Kumar, N.M.; Mukharib, D.S.; Mote, J.K.; Sudeesh, S.; Raj, U.; Raghuramulu, Y.; et al. National Level Inventory of Coffee Plantations Using High Resolution Satellite Data. The International

Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 2019, XLII-3/W6, 293–298. https://doi.org/10.5194/isprs-archives-XLII-3-W6-293-2019.

22. Bautista Calderon, E.A.; Ordaz Chaparro, V.M.; Gutiérrez Castorena, M.d.C.; Gutiérrez Castorena, E.V.; Cajuste Bontemps, L. Sistemas agroforestales de café en Veracruz, México: identificación y cuantificación espacial usando SIG, percepción remota y conocimiento local. Revista Terra Latinoamericana 2018, 36. https://doi.org/10.28940/terra.v36i3.350.
23. Kelley, L.C.; Pitcher, L.; Bacon, C. Using Google Earth Engine to Map Complex Shade-Grown Coffee Landscapes in Northern Nicaragua. Remote Sensing 2018, 10. https://doi.org/10.3390/rs10060952.
24. Tridawati, A.; Wikantika, K.; Susantoro, T.M.; Harto, A.B.; Darmawan, S.; Yayusman, L.F.; Ghazali, M.F. Mapping the Distribution of Coffee Plantations from Multi-Resolution, Multi-Temporal, and Multi-Sensor Data Using a Random Forest Algorithm. Remote Sensing 2020, 12, 3933. https://doi.org/10.3390/rs12233933.
25. Ortega-Huerta, M.A.; Komar, O.; Price, K.P.; Ventura, H.J. Mapping coffee plantations with Landsat imagery: an example from El Salvador. International Journal of Remote Sensing 2012, 33, 220–242. https://doi.org/10.1080/01431161.2011.591442.
26. Chemura, A.; Mutanga, O.; Odindi, J. Modelling Leaf Chlorophyll Content in Coffee (Coffea Arabica) Plantations Using Sentinel 2 Msi Data. In Proceedings of the IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2018, pp. 8228–8231. https://doi.org/10.1109/IGARSS.2018.8518848.
27. Figueroa-Hernández, E.; Pérez-Soto, F.; Godínez-Montoya, L. La produccion y el consumo del café. ECORFAN 2015, pp. 64–82.
28. INEGI. Continuo de elevaciones de México (CEM 3.0), 2019.
29. SMN. Resúmenes Mensuales de Temperaturas y Lluvia, 2019.
30. González-Espinosa, M.; Ramírez-Marcial, N.; Gómez-Pineda, E.; Parra-Vázquez, M.R.; Díaz-Hernández, B.M.; Musálem-Castillejos, K. Vulnerabilidad Ambiental y Social. Perspectivas de Restauración de Bosques en las Partes Altas de la Sierra

Madre de Chiapas. Investigación ambiental Ciencia y política pública 2015, 6, 90–91.

31. Moguel, P.; Toledo, V. Biodiversity Conservation in Traditional Coffee Systems of Mexico. Conservation Biology 1999, 13, 11–21.
32. Hernández-Stefanoni, J.L.; Castillo-Santiago, M.A.; Mas, J.F.; Wheeler, C.E.; Andres-Mauricio, J.; Tun-Dzul, F.; George-Chacón, S.P.; Reyes-Palomeque, G.; Castellanos-Basto, B.; Vaca, R.; et al. Improving aboveground biomass maps of tropical dry forests by integrating LiDAR, ALOS PALSAR, climate and field data. Carbon Balance and Management 2020, 15, 15. https://doi.org/10.1186/s13021-020-00151-6.
33. Brodu, N. Super-Resolving Multiresolution Images With Band-Independent Geometry of Multispectral Pixels. IEEE Transactions on Geoscience and Remote Sensing 2017, 55, 4610–4617. https://doi.org/10.1109/TGRS.2017.2694881.
34. Wu, C.; Niu, Z.; Tang, Q.; Huang, W. Estimating chlorophyll content from hyperspectral vegetation indices: Modeling and validation. Agricultural and Forest Meteorology 2008, 148, 1230–1241. https://doi.org/10.1016/j.agrformet.2008.03.005.
35. Haboudane, D.; Miller, J.R.; Tremblay, N.; Zarco-Tejada, P.J.; Dextraze, L. Integrated Narrow-band Vegetation Indices for Prediction of Crop Chlorophyll Content for Application to Precision Agriculture. Remote Sensing of Environment 2002, 81, 416–426. https://doi.org/10.1016/S0034-4257(02)00018-4.
36. Filipponi, F. Sentinel-1 GRD Preprocessing Workflow. Proceedings 2019, 18, 11. https://doi.org/10.3390/ECRS-3-06201.
37. Hunt, E.R.; Daughtry, C.; Eitel, J.U.H.; Long, D.S. Remote Sensing Leaf Chlorophyll Content Using a Visible Band Index. Agronomy Journal 2011, 103, 1090–1099. https://doi.org/10.2134/agronj2010.0395.
38. Main, R.; Cho, M.A.; Mathieu, R.; O'Kennedy, M.M.; Ramoelo, A.; Koch, S. An Investigation Into Iobust Spectral Indices for Leaf Chlorophyll Estimation. ISPRS Journal of Photogrammetry and Remote Sensing 2011, 66, 751–761. https://doi.org/10.1016/j.isprsjprs.2011.08.001.
39. Escadafal, R.; Belghith, A.; Ben-Moussa, H. Indices Spectraux Pour la Dégradation des Milieux Naturels en Tunisie Aride. In Proceedings of the 6e Symp. Int. sur les mesures physiques et signatures en teledetection, 1994, pp. 253–259.

40. Bannari, A.; Morin, D.; Bonn, F.; Huete, A.R. A Review of Vegetation Indices. Remote Sensing Reviews 1995, 13, 95–120. https://doi.org/10.1080/02757259509532298.
41. Darst, B.F.; Malecki, K.C.; Engelman, C.D. Using recursive feature elimination in random forest to account for correlated variables in high dimensional data. BMC Genetics 2018, 19, 65. https://doi.org/10.1186/s12863-018-0633-8.
42. Breiman, L. Random forests. Machine learning 2001, 45, 5–32. Publisher: Springer.
43. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Wulder, M.A. Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment 2014, 148, 42–57. https://doi.org/10.1016/j.rse.2014.02.015.
44. Olofsson, P.; Foody, G.M.; Stehman, S.V.; Woodcock, C.E. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sensing of Environment 2013, 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031.
45. Esri. World Imagery.
46. QGIS Development Team. QGIS Geographic Information System. Open-Source Geospatial Foundation, 2009.
47. Cordero-Sancho, S.; Sader, S.A. Spectral analysis and classification accuracy of coffee crops using Landsat and a topographic-environmental model. International Journal of Remote Sensing 2007, 28, 1577–1593. https://doi.org/10.1080/01431160600887680.
48. Maskell, G.; Chemura, A.; Nguyen, H.; Gornott, C.; Mondal, P. Integration of Sentinel optical and radar data for mapping smallholder coffee production systems in Vietnam. Remote Sensing of Environment 2021, 266, 112709. https://doi.org/https://doi.org/10.1016/j.rse.2021.112709.
49. Gomez, C.; Mangeas, M.; Petit, M.; Corbane, C.; Hamon, P.; Hamon, S.; De Kochko, A.; Le Pierres, D.; Poncet, V.; Despinoy, M. Use of high-resolution satellite imagery in an integrated model to predict the distribution of shade coffee tree hybrid zones. Remote Sensing of Environment 2010, 114, 2731–2744. Publisher: Elsevier.
50. Moreira, M.A.; Adami, M.; Rudorff, B.F.T. Spectral and temporal behavior analysis of coffee crop in Landsat images. Pesquisa Agropecuária Brasileira 2004, 39, 223–231. Publisher: SciELO Brasil.

51. Bernardes, T.; Moreira, M.A.; Adami, M.; Giarolla, A.; Rudorff, B.F.T. Monitoring Biennial Bearing Effect on Coffee Yield Using MODIS Remote Sensing Imagery. Remote Sensing 2012, 4, 2492–2509. https://doi.org/10.3390/rs4092492.
52. Marín-Garza, T.; Gómez-Merino, F.C.; Aguilar-Rivera, N.; Murguía-González, J.; Trejo-Téllez, L.I.; Pastelín-Solano, M.C.; Castañeda-Castro, O. Composición Bioactiva De Hojas De Café Durante Un Ciclo Anual. Revista Fitotecnia Mexicana 2018, 41, 365–372. https://doi.org/10.35196/rfm.2018.4.365-372.
53. Castañeda-Castro, O. Variaciones en Área Foliar y Concentraciones de Clorofilas y Nutrimentos Esenciales en Hojas de Café Robusta (Coffea Canephora P.) Durante un Ciclo Anual. Agro Productividad 2018, 11. https://doi.org/10.32854/agrop.v11i4.266.
54. Júnior, A.F.C.; de Carvalho Júnior, O.A.; de Souza Martins, E.; Guerra, A.F. Phenological characterization of coffee crop (Coffea arabica L.) from MODIS time series. Brazilian Journal of Geophysics 2013, 31, 569–578.
55. Ruiz-de Oña, C.; Merlín-Uribe, Y. New Varieties of Coffee: Compromising the Qualities of Adaptive Agroforestry? A Case Study from Southern Mexico. Frontiers in Sustainable Food Systems 2021, 5, 123. Publisher: Frontiers.

Discusión

Los resultados del trabajo de investigación mostraron que en el área de estudio las parcelas de café tienen en promedio una extensión de 1.5 hectáreas dispersas de manera heterogénea, mayormente en las áreas de bosque degradado o de vegetación secundaria. Principalmente, para el establecimiento de los SAF, se buscó la utilización de la vegetación ya presente en las áreas de cultivo como sombra para el cultivo del café, aunque es común la introducción de especies frutales para autoconsumo y maderables para extracción de leña.

Como sistema agroforestal, el cultivo del café ha sufrido varias modificaciones a lo largo de los últimos años en respuesta a factores ambientales y económicos. Como respuesta a plagas y enfermedades como la Roya (*Hemileia vastatrix*) se ha ido gradualmente modificando el porcentaje total de cobertura sobre los cultivos, la cantidad de estratos de vegetación sobre las plantas de café y se han cambiado las variedades cultivadas. En consecuencia, la identificación de estos cultivos bajo las categorías propuestas por Moguel y Toledo (1999), no fue posible, por lo que se definieron tres categorías específicas para los SAF de café en el área de estudio. Para la definición de estas categorías, se consideró la respuesta espectral de los cultivos, con el fin de aportar más información para una clasificación más precisa.

Los sistemas agroforestales rústicos fueron los de mayor presencia en el área de estudio, posiblemente debido a que el difícil acceso a las áreas de cultivo y la alta heterogeneidad topográfica no permite una mayor tecnificación del cultivo; sin embargo, se aprovecha la vegetación presente como sombra en los cafetales, por lo que se ubican mayormente en áreas adyacentes a bosques maduros. Los policultivos rústicos presentaron una extensión total similar a los sistemas rústicos, principalmente porque se busca la diversidad productiva para aumentar los ingresos económicos totales, como compensación a la baja producción obtenida en ciclos anteriores por plagas e incendios. A pesar de la menor extensión de policultivos con sombra reducida, en los últimos años se ha visto un crecimiento en su implementación debido, principalmente, a factores económicos, por lo que se busca incrementar la producción al aumentar la densidad de plantas de café y de especies introducidas y reducir la densidad de árboles nativos. En consecuencia, existe un riesgo para la conservación de los ecosistemas forestales en la región.

Conclusión

En este trabajo de investigación se implementó un enfoque multitemporal donde se realizó un análisis particular para cada tipo de sistema agroforestal de café considerando la respuesta espectral individual. Los resultados obtenidos son significativos dada las limitaciones y los valores de precisión mostrados en estudios previos de áreas de producción de café con estructura arbórea y topografía similares. El uso de conjuntos de predictores diferentes, definidos a través de algoritmos de optimización de predictores mostró valores de precisión más altos en contraste con el uso convencional de datos de sensores remotos considerando los periodos óptimos para la recolección de datos de sensores remotos. La identificación de diferentes tipos de SAF aporta al estudio de la dinámica alteración del paisaje asociada a la producción de café, en relación con limitaciones ambientales y las prácticas agroforestales.

Estudios posteriores podrían encaminarse a utilizar la metodología descrita en este trabajo de investigación en otras áreas de producción de café bajo prácticas de cultivo diferentes y bajo con condiciones topográficas y de vegetación distintas y evaluar la precisión del modelo en diferentes paisajes. Por otro lado, en el procedimiento llevado a cabo para el mapeo de SAF únicamente se utilizaron conjuntos diferenciados únicamente para los tres tipos de sistemas; estudios posteriores pueden enfocarse a ampliar la definición de conjuntos específicos para otras clases de cobertura vegetal o sistemas de producción agrícola para reducir la incertidumbre en la clasificación.

Referencias

Baghdadi N, Mehrez Z. 2016. Optical Remote Sensing of Land Surface. Elsevier. https://linkinghub.elsevier.com/retrieve/pii/C20150012205.

Blaschke T. 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing. 65(1):2–16. doi:https://doi.org/10.1016/j.isprsjprs.2009.06.004.

Boell M, Ramos Alves H, Volpato M, Ferreira D, Lacerda W. 2018. Exploiting Feature Extraction Techniques for Remote Sensing Image Classification. IEEE Latin America Transactions. 16(10):2657–2664. doi:10.1109/TLA.2018.8795147.

Borelli S, Conigliaro M, Olivier E. 2017. Agroforesteria para la restauración del paisaje: explorando el potencial de la agroforesteria para mejorar la sostenibilidad y la resiliencia de los paisajes degradados. FAO.

D’Negri CE, De Vito EL. 2006. Introducción al razonamiento aproximado: lógica difusa. Revista Americana de Medicina Respiratoria. 6(3):126–136.

Farfán-Valencia F. 2019. Descripción de la Estructura del Dosel Arbóreo al Interior de un Sistema Agroforestal con Café. Manizales, Caldas, Colombia: Centro Nacional de Investigaciones de Café.

Figueroa-Hernández E, Pérez-Soto F, Godínez-Montoya L, Perez-Figueroa RA. 2019. Los precios de café en la producción y las exportaciones a nivel mundial. Revista mexicana de economía y finanzas. 14(1):41–56.

Flores Vichi F. 2015. La producción de café en México: ventana de oportunidad para el sector agrícola de Chiapas. Revista Espacio I+D Innovación más Desarrollo. 4(7):174–194. doi:10.31644/IMASD.7.2015.a07.

Hebbar R, Ravishankar HM, Trivedi S, Manjula VB, Kumar NM, Mukharib DS, Mote JK, Sudeesh S, Raj U, Raghuramulu Y, et al. 2019. National Level Inventory of Coffee Plantations Using High Resolution Satellite Data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XLII-3/W6:293–298. doi:10.5194/isprs-archives-XLII-3-W6-293-2019.

Higuera-Ciapara I, Rivera-Ramírez J. 2018. Chiapas: Problemáticas del Sector Cafetalero. Guadalajara: Centro de Investigación y Asistencia en Tecnología y Diseño del Estado de Jalisco.

Hunt, Tabor K, Hewson JH, Wood MA, Reymondin L, Koenig K, Schmitt-Harsh M, Follett F. 2020. Review of Remote Sensing Methods to Map Coffee Production Systems. Remote Sensing. 12(12):2041. doi:10.3390/rs12122041.

INCAFECH. 2019. El café en México. Assets INCAFECH.:1–7.

Jose S. 2019. Environmental Impacts and Benefits of Agroforestry. In: Oxford Research Encyclopedia of Environmental Science. Oxford University Press. https://oxfordre.com/environmentalscience/view/10.1093/acrefore/9780199389414.001.0001/acrefore-9780199389414-e-195.

Kelley LC, Pitcher L, Bacon C. 2018. Using Google Earth Engine to Map Complex Shade-Grown Coffee Landscapes in Northern Nicaragua. Remote Sensing. 10(6):952. doi:10.3390/rs10060952.

Maskell G, Chemura A, Nguyen H, Gornott C, Mondal P. 2021. Integration of Sentinel optical and radar data for mapping smallholder coffee production systems in Vietnam. Remote Sensing of Environment. 266:112709. doi:https://doi.org/10.1016/j.rse.2021.112709.

Moguel P, Toledo V. 1999. Biodiversity Conservation in Traditional Coffee Systems of Mexico. Conservation Biology. 13(1):11–21.

Montagnini F, Somarriba E, Murgueitio E, Fassola H, Eibl B. 2015. Función de los sistemas agroforestales en la adaptación y mitigación del cambio climático. In: Sistemas agroforestales. Funciones productivas, socioeconómicas y ambientales. Turrialba, Costa Rica: CATIE. p. 269–298.

Moser G, Serpico SB, Benediktsson JA. 2013. Land-Cover Mapping by Markov Modeling of Spatial–Contextual Information in Very-High-Resolution Remote Sensing Images. Proceedings of the IEEE. 101(3):631–651. doi:10.1109/JPROC.2012.2211551.

Mosomtai G, Odindi J, Abdel-Rahman EM, Babin R, Fabrice P, Mutanga O, Tonnang HEZ, David G, Landmann T. 2020. Landscape Fragmentation in Coffee Agroecological Subzones in Central Kenya: A Multiscale Remote Sensing Approach. Journal of Applied Remote Sensing. 14(04). doi:10.1117/1.JRS.14.044513. https://www.spiedigitallibrary.org/journals/journal-of-applied-remote-sensing/volume-14/issue-04/044513/Landscape-fragmentation-in-coffee-agroecological-subzones-in-central-Kenya/10.1117/1.JRS.14.044513.full.

Mukashema A, Veldkamp A, Vrieling A. 2014. Automated High Resolution Mapping of Coffee in Rwanda Using an Expert Bayesian network. International Journal of Applied Earth Observation and Geoinformation. 33:331–340. doi:10.1016/j.jag.2014.05.005.

Muschler RG. 2016. Agroforestry: Essential for Sustainable and Climate-Smart Land Use? In: Tropical Forestry Handbook. Berlin, Heidelberg: Springer Berlin Heidelberg. p. 2013–2116. http://link.springer.com/10.1007/978-3-642-54601-3_300.

Richards JA. 2009. Remote Sensing with Imaging Radar. Berlin, Heidelberg: Springer Berlin Heidelberg (Signals and Communication Technology). http://link.springer.com/10.1007/978-3-642-02020-9.

Rizvi RH, Dhyani SK, Newaj, R., Saxena A, Karmakar PS. 2013. Mapping extent of agroforestry area through remote sensing: issues, estimates and methodology. Indian Journal of Agroforestry. 15(2):26–30.

Ruvalcaba Coyaso FJ, Vermonden A. 2016. Lógica difusa para la toma de decisiones y la selección de personal. Universidad & Empresa. 17(29):239–256. doi:10.12804/rev.univ.empresa.29.2015.10.

Sarmiento CM, Ramirez GM, Coltri PP, Silva LFL e, Nassur OAC, Soares JF. 2014. Comparação de classificadores supervisionados na discriminação de áreas cafeeiras em Campos Gerais - Minas Gerais. Coffee Science. 9:546–557.

Schmitt-Harsh M, Sweeney SP, Evans TP. 2013. Classification of Coffee-Forest Landscapes Using Landsat TM Imagery and Spectral Mixture Analysis. Photogrammetric Engineering & Remote Sensing. 79(5):457–468. doi:10.14358/PERS.79.5.457.

Souza CG, Carvalho L, Aguiar P, Arantes TB. 2016. Algoritmos de Aprendizagem de Máquina e Variáveis de Sensoramento Remoto para o Mapamento da Cafeicultura. Boletim de Ciências Geodésicas. 22(4):751–773. doi:10.1590/s1982-21702016000400043.

Souza VCO, Castro YB, Paula MMV, Volpato MML. 2018. Demarcafé: a proposal to support the mapping of coffee areas using citizen science. Proceedings of the XIV Brazilian Symposium on Information Systems. https://api.semanticscholar.org/CorpusID:262587883.

Tridawati A, Wikantika K, Susantoro TM, Harto AB, Darmawan S, Yayusman LF, Ghazali MF. 2020. Mapping the Distribution of Coffee Plantations from Multi-Resolution, Multi-Temporal, and Multi-Sensor Data Using a Random Forest Algorithm. Remote Sensing. 12(23):3933. doi:10.3390/rs12233933.

Tso B, Mather PM. 1999. Crop discrimination using multi-temporal SAR imagery. International Journal of Remote Sensing. 20(12):2443–2460. doi:10.1080/014311699212119.

Valencia V, García-Barrios L, Sterling EJ, West P, Meza-Jiménez A, Naeem S. 2018. Smallholder response to environmental change: Impacts of coffee leaf rust in a forest frontier in Mexico. Land Use Policy. 79:463–474. doi:10.1016/j.landusepol.2018.08.020.

Villavicencio-Enríquez L. 2013. Caracterización agroforestal en sistemas de café tradicional y rústico, en San Miguel, Veracruz, México. Revista Chapingo Serie Ciencias Forestales y del Ambiente. XIX(1):67–80. doi:10.5154/r.rchscfa.2010.08.051.

Zapata Arango PC. 2019. Composición y estructura del dosel de sombra en sistemas agroforestales con café de tres municipios de Cundinamarca, Colombia. Ciência Florestal. 29:685–697.