

## A review of PlanetScope CubeSats for forest monitoring

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### ABSTRACT

Satellite remote sensing has been a cornerstone of forest monitoring, enabling the observation of extensive areas at regular intervals. In 2014, Planet Labs introduced PlanetScope, a constellation of Earth observation CubeSats capable of delivering near-daily optical data at a 3 m resolution across the globe. The unique combination of high temporal and spatial resolution, along with comprehensive coverage, positions PlanetScope as a valuable tool for a wide range of forestry applications. This systematic literature review explores the diverse applications of PlanetScope in forestry research, detailing the ecosystems studied, the spatial and temporal characteristics of the datasets, analytical methods employed, and integration with other remote sensing technologies. We comment on potential strengths and weaknesses of the available datasets, compare models developed using PlanetScope with those derived from other remote sensing data sources, identify key areas for future research, and finally provide recommendations and considerations for prospective users of PlanetScope data.

### 1. Introduction

Since the launch of the first Landsat satellite in 1972, satellite-based remote sensing systems have become indispensable for large-scale environmental monitoring (Boyd and Danson, 2005; Onoda and Young, 2017). In the study of forests, optical satellite imagery—images captured by passive sensors that detect reflected sunlight in visible and infrared wavelengths—has been used to map forest cover; detect changes; and model a diverse array of attributes related to forest health, structure, biodiversity, biomass, and soil characteristics (Lechner et al., 2020). From a practical standpoint, satellite-based optical systems provide data which is usually cheaper to acquire than that of aerial systems and less complicated to analyze than that of active remote sensing systems (Lechner et al., 2020). The rich history of optical satellites for forest monitoring has also resulted in a significant historical archive of land cover and land use patterns (Wulder et al., 2022).

A relatively recent innovation in satellite remote sensing has been the development of CubeSats. Constructed using one or more cube-shaped modules with standard dimensions of 10 cm × 10 cm × 10 cm and a typical mass of 1.5 kg (Sweeting, 2018; Villela et al., 2019), CubeSats are much smaller than other satellites which have been traditionally used for remote sensing (Curnick et al., 2021; Sweeting,

2018). Owing to their diminutive size, CubeSats are relatively inexpensive to produce and launch (Curnick et al., 2021); moreover, they can be put into orbit more quickly than traditional satellites because they can be launched in relatively high volumes or carried into orbit as a secondary payload (Sweeting, 2018). The advantageous economy of CubeSats means that they are usually deployed in constellations of satellites which collectively produce imagery with short revisit intervals (Sweeting, 2018).

To date, the largest constellation of CubeSats used for Earth observation is PlanetScope, a network of commercial satellites owned by Planet Labs PBC which are equipped with multispectral sensors. The first generation—or “flock”—of PlanetScope satellites was launched back in 2014; since then, additional flocks have been launched with updated instruments (Frazier and Hemingway, 2021). As of July 25th 2025, there were 118 active satellites in the PlanetScope constellation (Bahloul et al., 2025).

With more conventional satellite remote sensing systems—which normally consist of one or two satellites carrying sensors fixed near-nadir—there is usually a trade-off between spatial and temporal resolution since the altitude of a sensor is inversely proportional to its swath width (Colwell, 1983; Zhang and Kerle, 2008). Some satellites with high spatial resolution (e.g. SkySat, Quickbird, Worldview) are able to

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overcome this trade-off by altering their view angle to revisit areas; however, these are unsuitable for developing archives of data which are both spatially comprehensive and geometrically consistent. By integrating data acquired by many dozens of CubeSats, PlanetScope is able to provide high resolution imagery (less than 4.2m) of the entire surface of the Earth with a revisit time of approximately 1 day (Planet Labs, 2022, 2023a). Taken individually, there are other optical remote sensing technologies which meet or exceed each of these parameters; for instance, the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on the TERRA and AQUA satellites provide global coverage with a similar revisit time, while the Worldview series of satellites provides optical imagery at spatial resolutions below 2 m. However, the combination of these factors makes PlanetScope a unique system with significant potential for detecting or characterizing fine-scale forest changes (Coops et al., 2022).

While its high temporal and spatial resolution make PlanetScope a promising technology for forest monitoring and mapping, there are challenges associated with using this data. Relative to more traditional satellite systems, PlanetScope data can have lower image quality as a result of lower radiometric consistency, lower geometric consistency, or a higher incidence of anomalous pixels (Frazier and Hemingway, 2021; Keay et al., 2022). PlanetScope also detects a more restricted range of wavelengths than some other commonly used satellite sensors. In particular, it lacks bands in the shortwave infrared and thermal infrared portions of the spectrum, which are used in a host of forest monitoring applications (Li et al., 2022; Smigaj et al., 2023; Zeng et al., 2022) as well as being useful for issues such as cloud detection (Zhu and Woodcock, 2012).

Our objective in this review is to examine the use of PlanetScope for forest-focused applications since the constellation's launch including the forest ecosystems, phenomena, and attributes PlanetScope has been used to study, and the spatiotemporal characteristics of the PlanetScope datasets used in these studies. Next, we review the use of PlanetScope data in conjunction with other remote sensing datasets and the extent to which models trained using PlanetScope data perform relative to other remote sensing datasets. We also review the most common approaches and algorithms used to process PlanetScope data, as well as different methods for addressing PlanetScope's data quality issues. Finally, we assess how PlanetScope data have been leveraged for near-real time monitoring and precision forestry. We conclude by discussing knowledge gaps and highlighting potential future directions for the continued successful application of this technology in the forest domain.

## 2. Technical overview of PlanetScope

### 2.1. Platform and sensor characteristics

PlanetScope is a constellation of CubeSats owned by Planet Labs PBC (Planet Labs, 2023b). Each individual satellite—which are called Doves—measures 30 cm × 10 cm × 10 cm, has a mass of 5.8 kg (Kim et al., 2022; Planet Labs, 2023a) and orbits sun-synchronously at an altitude of 450–580 km and an inclination of 98°, allowing them to capture imagery between approximately 81.5° latitude north and south (Planet Labs, 2023a). The position of PlanetScope satellites in low-earth orbit contributes to their high spatial resolution, relatively small frame size, and short revisit time (Table 1). As of 2021, the global median average revisit time for PlanetScope was 30.3 h (Roy et al., 2021), which varies as new satellites are launched and older satellites are decommissioned. As opposed to many other Earth observation satellites (such as the Landsat and Sentinel platforms) which use a push-broom sensor for continuous data acquisition, PlanetScope satellites are equipped with a frame imager that acquires data in discrete, partially-overlapping frames (Kääb et al., 2019).

Since the inception of PlanetScope, a number of different “flocks”—groups of similar satellites—have been launched by Planet Labs in order to expand the constellation, implement technological

**Table 1**

Characteristics of the three generations of PlanetScope satellites and sensors. Adapted from Planet Labs (2023a).

Satellite and instrument name	Operation timeline	Bands (nm)	Frame size (km)	Orbit altitude (km)	Ground sample distance (m)
Dove Classic PS2	July 2014–April 2022	Blue (455–515) Green (500–590) Red (590–670) NIR (780–860)	24.0 × 8.0	450–580	3.0–4.1
Dove-R PS2.SD	March 2019–April 2022	Blue (464–517) Green (547–585) Red (650–682) NIR (846–888)	24.0 × 16.0	450–580	3.0–4.1
Super Dove PSB.SD	March 2020 – present	Coastal Blue (431–452) Blue (465–515) Green I (513–549) Green (547–583) Yellow (600–620) Red (650–680) RE (697–713) NIR (845–885)	32.5 × 19.6	475–525	3.7–4.2

improvements, or replace satellites that have reached their end-of-life. These flocks are divided into three generations of satellites—called Dove Classic, Dove-R, and Super Dove—differentiated based on the type of sensor they carry (Table 1).

The Dove Classic satellites were first launched in 2014 and remained active until April 2022 (Planet Labs, 2023a). The earliest images available in the PlanetScope archive are from 2013; however, the constellation did not begin to regularly provide near-complete global coverage until 2017 (Frazier and Hemingway, 2021). The PS2 instrument onboard the Dove Classic satellites featured a split-frame sensor for detecting 4 spectral bands—blue, green, red, and near-infrared—with marked overlap between the wavelengths detected by each of the visible bands (Frazier and Hemingway, 2021; Planet Labs, 2023a).

The second generation of PlanetScope satellites—Dove-R—were launched in 2018 and remained active until April 2022 (Planet Labs, 2023a). The PS2.SD instrument onboard these satellites featured a “butcher’s block filter” for detecting RGB-NIR imagery in narrower spectral bands than the Dove Classic satellites, thus eliminating spectral band overlap (Frazier and Hemingway, 2021). Both the Dove Classic and the Dove-R satellites orbited the Earth at altitudes ranging from 450 to 580 km and spatial resolutions between 3.0 and 4.1 m (Planet Labs, 2023a).

The third generation of PlanetScope satellites—the Super Doves—were first launched in 2019 (Planet Labs, 2023a). Like the PS2.SD instrument of the Dove-Rs, their PSB.SD instrument also features a “butcher’s block filter”, designed to detect 8 spectral bands. Four of these 8 bands (blue, red, green, NIR) are similar to those detected by the Dove-Rs, while 6 of the 8 bands (coastal blue, blue, green, red, red edge, NIR) correspond to bands 1–5 and 8a of the Sentinel-2 satellites (Planet Labs, 2023c). Relative to the earlier generations, the Super Doves orbit

the Earth in a narrower range of altitudes (475–525 km) and have a slightly coarser spatial resolution (3.7–4.2m). As of March 2025, since all remaining satellites from the first two generations were decommissioned in April 2022, the only operational satellites in the PlanetScope constellation are Super Doves.

## 2.2. Data products

Depending on the acquisition date and instrument used, PlanetScope produces a range of publicly available data products (“levels”) covering different spectral band combinations and degrees of preprocessing (Table 2; Planet Labs, 2022; 2023a). The baseline public product is “Basic Scene” (level 1B) which represents top-of-atmosphere radiance, is not orthorectified, and has a spatial resolution equivalent to the ground-sample distance of the raw imagery. The “Ortho Scene” products (level 3B) are orthorectified using a network of ground control points, projected to a common map projection, and resampled to a 3 m pixel size. Ortho Scenes are available in two main varieties, with the “Visual” product limited to RGB bands and receiving color correction, while the “Analytic” product has the full complement of 4 or 8 bands (depending on the model of satellite acquiring it) and is available as either top-of-atmosphere radiance or surface reflectance for quantitative analysis. Both the Basic Scene and Ortho Scene products represent a single frame captured by a PlanetScope sensor; until March 2023, Planet also produced Ortho Tile products (levels 3A and 5A), where imagery was clipped to a standardized grid. All PlanetScope image products are published with metadata and Useable Data Masks (UDM), which are generated using supervised machine learning algorithms (Planet Labs, 2024a).

Planet Labs also produces a variety of basemap products for monitoring large spatial areas by selecting the highest quality images from a time series of PlanetScope Ortho Scenes, applying additional radiometric normalization to remove seamlines between images, and mosaicking the resulting images (Planet Labs, 2024b). These basemaps are currently available at weekly, monthly, and quarterly timesteps as both visual or analytic products.

## 3. Literature review methods

To analyze the use of PlanetScope data in forest monitoring, we conducted a literature search within the Web of Science and SCOPUS core collections. We searched the abstracts, titles, and keywords of journal articles for terms relating to “planet”, “planetscope”, “dove”, “superdove”, “cubesat” and “forest”. We did not include government reports, dissertations, or other forms of grey literature and only included

**Table 2**  
Characteristics of different PlanetScope data products currently available in Planet Labs’ digital archive. Table adapted from (Planet Labs, 2022, 2023a).

Product attribute	Basic Scene	Ortho Scene		Basemap	
Product type	–	Visual	Analytic	Visual	Analytic
Bands	All PS2, PS2.SD, PSB.SD	RGB	All PS2, PS2.SD, PSB.SD	RGB	All PS2, PS2.SD, PSB.SD
Pixel size (m)	PS2: 3.0–4.1 PS2.SD: 3.0–4.1 PSB.SD: 3.7–4.2	3.0	3.0	≤4.77	≤4.77
Bit depth (bits)	DN: 12 Radiance: 16	8	16	8	16
Orthorectified	No	Yes	Yes	Yes	Yes
Map projection	None	UTM/ WGS84	UTM/ WGS84	Web Mercator/ WGS84	Web Mercator/ WGS84

articles written in English. All articles published in 2024 or earlier were considered for inclusion. The resulting articles from each database were extracted and combined into a single list, and duplicate items were removed. Articles that did not contain the word “forest” in the title or abstract were automatically removed. Articles where the word “forest” only appeared within the term “random forest” were also automatically removed, since random forest is a popular machine learning algorithm which may have applications unrelated to forestry. Each article was then read and assessed for relevance, removing any invalid articles and extracting key information about each study. These attributes are listed in Table 3.

## 4. Results

The initial database queries returned 819 unique academic articles, which was reduced to 157 after filtering (Fig. 1). Fifteen of these are conference papers, all others are articles in academic journals.

### 4.1. Publication trends

The number of articles annually increased near-linearly from 9 in 2018—the earliest publication year for which articles could be found—to 46 in 2024 (Fig. 2). The oldest PlanetScope data used by articles in the review list was acquired in 2015, one year after the constellation was first launched (Baloloy et al., 2018; Pascual et al., 2022; Takasaki et al., 2022).

Eighteen percent of articles use PlanetScope data to validate an analysis accomplished using coarser resolution remote sensing data. PlanetScope is ideal for this purpose because its short revisit time means that high-resolution imagery can often be acquired on the same day as other satellite data. However, the increasing use of PlanetScope data appears to be driven by articles which analyze the data itself rather than using it for validation (Fig. 2).

### 4.2. Locations and ecosystems

PlanetScope data has been utilized in forest studies in 98 countries

**Table 3**  
Information gleaned from each article in the final review list.

Attribute	Definition
Application	The physical phenomenon being imaged or modelled using PlanetScope imagery.
Region	Continent and country for which PlanetScope imagery was analyzed
Ecosystems	The terrestrial biomes (Olson et al., 2001) which intersect the study area.
Size	Spatial extent of the study area.
Data product	PlanetScope data product used, indicating the level of preprocessing completed by Planet Labs.
Temporal resolution	Average frequency of PlanetScope data used in time-series analysis, measured in days.
Features	The set of variables derived from PlanetScope data which were used for analysis.
Radiometric correction	Whether additional radiometric correction was applied to the data, and if so, the method used.
Other remote sensing data	What other remote sensing data were used in each article.
Role of PlanetScope	Whether PlanetScope imagery was the main data used in the analysis or if it was only used for validation.
Complementary or comparison	Whether the purpose of the article was to develop a single model by integrating PlanetScope with other remote sensing data or to develop and compare multiple models using data from different sensor/platform combinations.
Analysis method	The procedure or algorithm used to analyze the PlanetScope data.
Analysis performance	The accuracy, goodness-of-fit, p-value, or strength of correlation for the analysis method applied to the PlanetScope data.

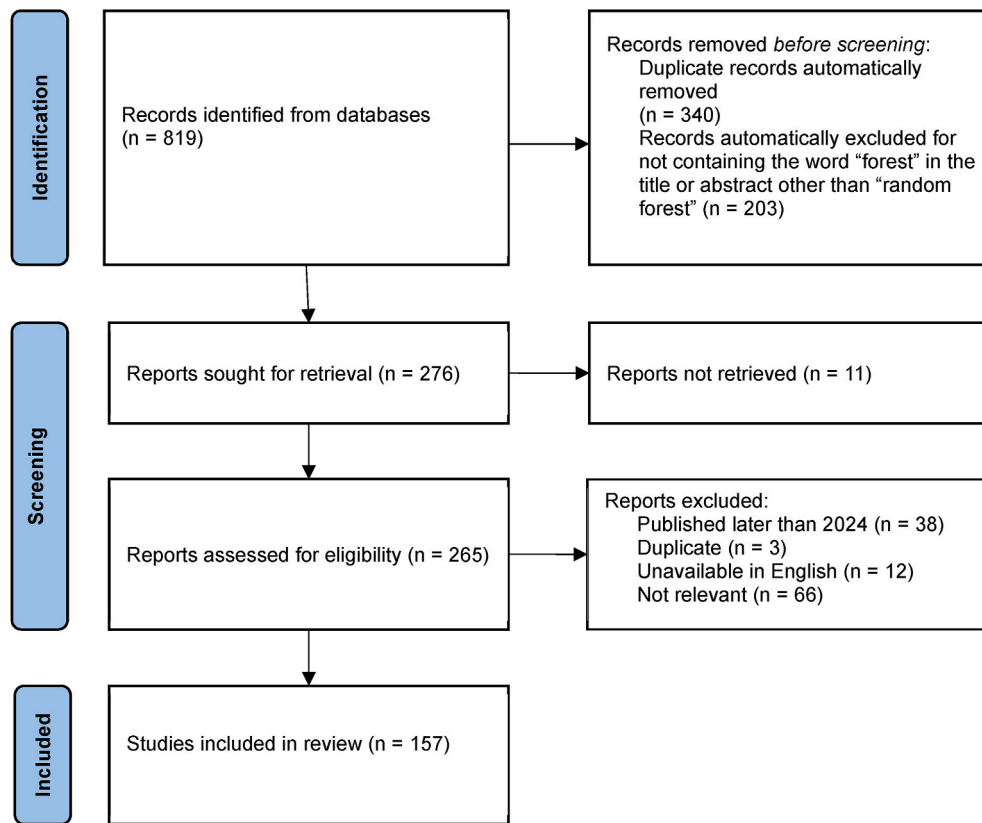


Fig. 1. PRISMA diagram outlining the process for selecting articles. Filtering steps are conducted in the order listed on the right.

(Fig. 3). Most research using PlanetScope data has focused on tropical regions, including the Amazon rainforest, the Congo Basin, and areas around the South China Sea. The most commonly featured country is Brazil (appearing in more than twice as many articles as the two countries tied for second place: Peru and the United States). PlanetScope has been used to study many types of terrestrial ecosystems (Fig. 8) with 46 % of articles examining tropical forests, 29 % examining temperate coniferous or broadleaf forests, 35 % examining trees in non-forested ecosystems such as grasslands or deserts, and 9 % looking at anthropogenic ecosystems such as plantations or urban greenspace (note that individual articles may include multiple different ecosystems). Only 8 articles (5 %) used PlanetScope to study high-latitude boreal forests.

### 4.3. Dataset characteristics

#### 4.3.1. Temporal characteristics of datasets

Time series of remote sensing data are frequently used for detecting abrupt change events or analyzing long-term trends (Gómez et al., 2016). Seventy-eight articles analyzed time series of PlanetScope data. Temporal ranges (the time between the first and last dates in the series) varied between 1 day (Weżyk et al., 2019) and 6 years (Y. Wang et al., 2023), with a median length of 1 year (Fig. 4). The median number of images over these time series was 12, with a median time interval between images of 29 days (Fig. 4). Fourteen articles used imagery taken from two dates to detect changes, while the remainder used multiple dates to monitor trends. Articles were primarily focused on monitoring different types of forest disturbances or tracking phenological trends. In general, the temporal resolution for phenological applications is higher than that of disturbance monitoring, with median revisit times on the scale of weeks and months respectively. However, there is typically a large range in temporal resolutions for different applications. For mapping of harvesting events, Keay et al. (2022) used a dense time series of PlanetScope scenes with an average revisit time of 3 days to detect

harvest data in Ontario, Canada, while Ygorra et al. (2021a) used two images acquired two years apart for the same purpose in the Congo. Dixon et al. (2021) used a time series with an average revisit time of 2 days for predicting tree flowering in Australia, while Ruiz-Díaz et al. (2024) used monthly imagery for analyzing landscape phenology in a Paraguayan dry forest. The longest time series of PlanetScope data is presented by Y. Wang et al. (2023), who used two images taken 6 years apart to evaluate mangrove restoration at a site in southern China. In this review, only one article had an average revisit time of one day: Weżyk et al. (2019) used a time series consisting of two images on consecutive days to evaluate forest damage following a hurricane in northern Poland. However, many other articles (Francini et al., 2020; Keay et al., 2022) report using some images from consecutive days, so the short revisit time reported by Weżyk et al. (2019) can be attributed to the fact that they also used the shortest time series in the review.

Virtually all articles which use PlanetScope time series data include a preprocessing step where low quality images are filtered out, either manually by inspecting the images or automatically using their metadata. The proportion of useable PlanetScope images varies seasonally due to factors which affect image quality (such as clouds, snow, or shadows resulting from sun angle). Galvão et al. (2023) report acquiring useable images on a daily or weekly basis during the dry season but less than one useable image per month during the wet season for many sites in the Amazon. This lack of useable data leads to restricted analysis throughout the year. Zhao et al. (2023) used PlanetScope imagery acquired during the first 250 calendar days of each year from 2017 to 2020 to analyze spring leaf phenology in an eastern North American hardwood forest.

An important caveat when reviewing the temporal resolution of PlanetScope data is that different studies use different definitions of “image quality” to retain or reject an image. For instance, while many articles use images which cover the entire study area, Zhao et al. (2022) used images which covered at least 50 % of their study sites. In addition,

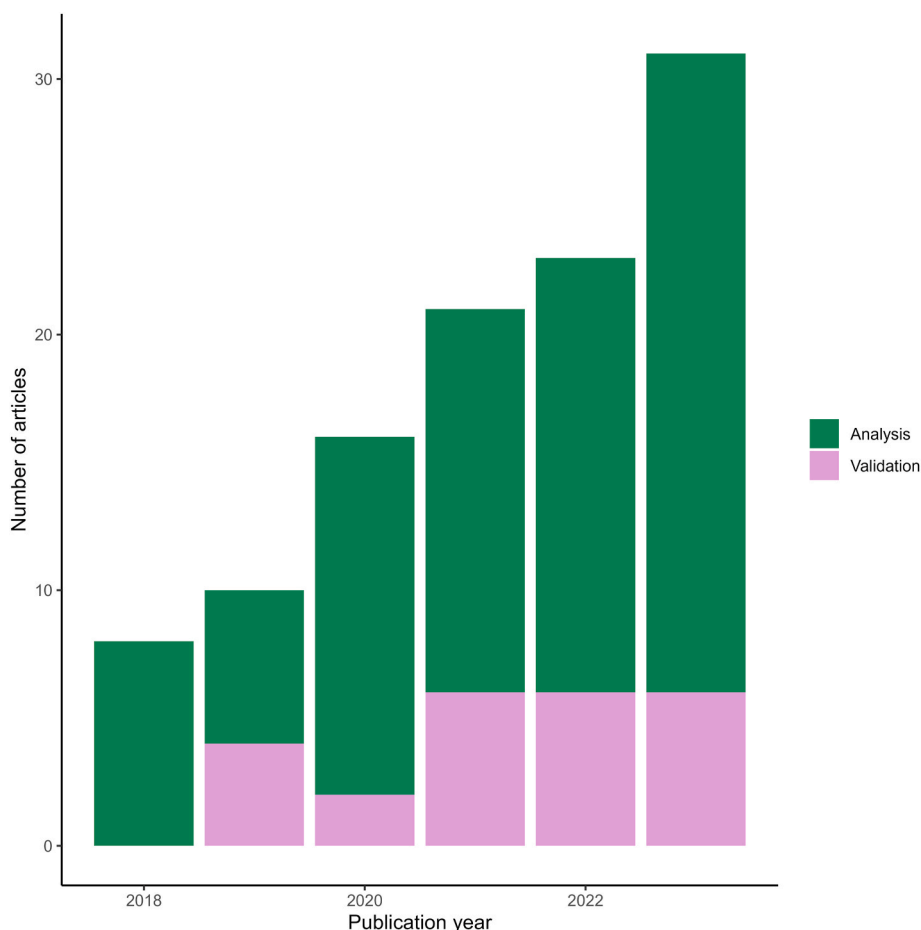


Fig. 2. Total number of articles published from 2018 (the earliest year for which articles are available) to 2024 which use PlanetScope data for an analytic purpose (green) or which use PlanetScope for visual validation of another method.

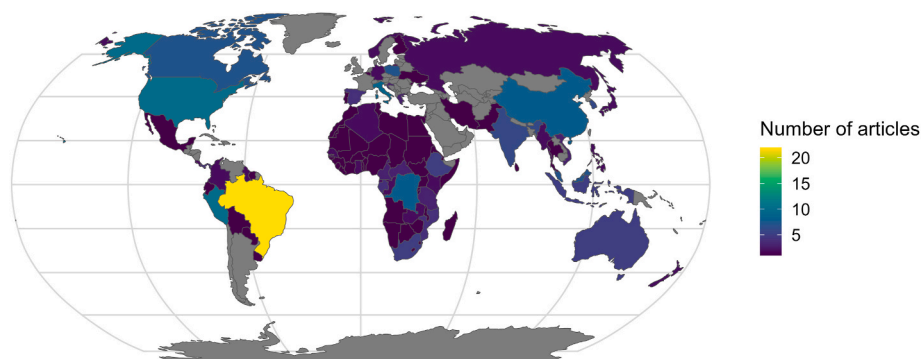


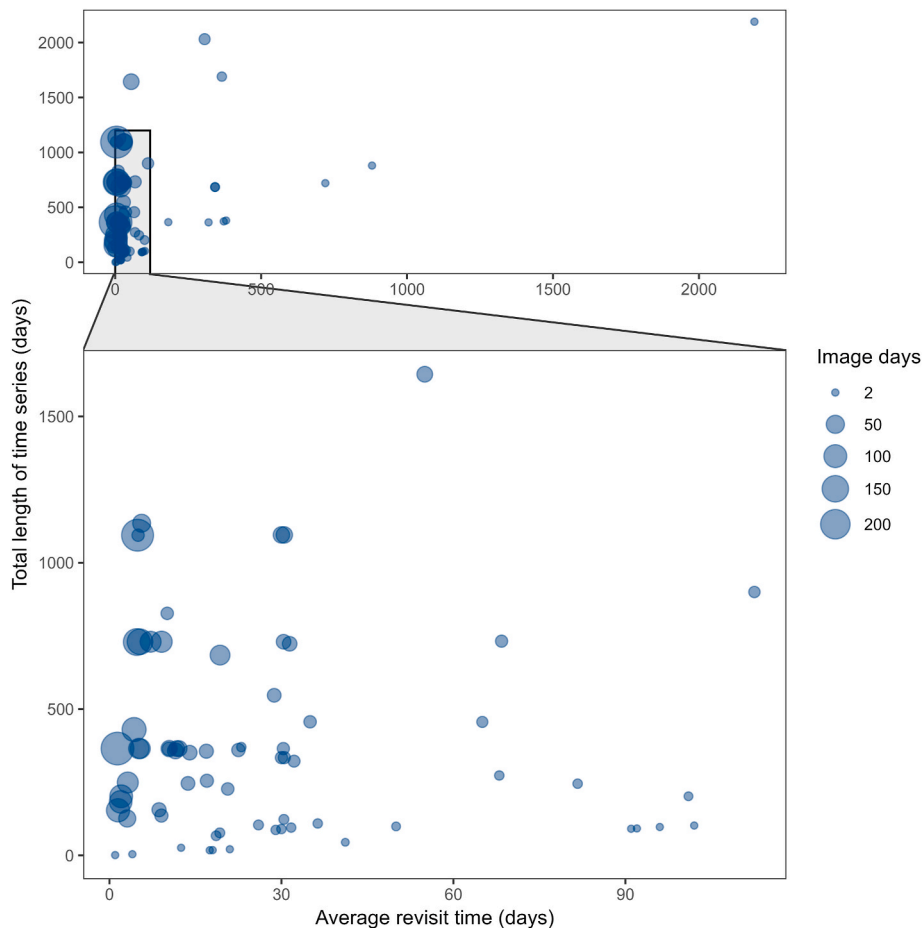
Fig. 3. Number of articles that use PlanetScope data to study areas in each country. Individual articles may use PlanetScope data from multiple countries.

many articles retain only clear-sky images for use by either manually screening their data or automatically filtering out cloud-contaminated images with the UDM layers that accompany PlanetScope data. Ygorra et al. (2021b) maximized the number of images used in the analysis by accepting images which were covered in haze or thin cloud but still allowed forest disturbances in the Congo to be manually delineated.

#### 4.3.2. Spatial characteristics of datasets

With respect to analysis area, the median area imaged across the studies was 128 km<sup>2</sup>. The majority of articles use PlanetScope data for studying areas which are smaller than a single PlanetScope scene, which range in size from 192 to 637 km<sup>2</sup> depending on the generation of

satellite that acquired it (Table 1, Fig. 5). However, the total area imaged using PlanetScope in individual articles span many orders of magnitude. At the small end, Pan et al. (2024) compared PlanetScope with Sentinel-2 and Landsat for characterizing forest phenology in a single 30 m × 30 m sampling plot, an area equivalent to 100 pixels from a PlanetScope Scene product. In contrast, PlanetScope data has also been used to model biomass and canopy cover across the entire nation of Peru (approximately 1.3 million km<sup>2</sup>; Csillik et al., 2019, 2020; Csillik and Asner, 2020b, 2020a), and Reiner et al. (2023) used PlanetScope to map tree cover across the entire continent of Africa (over 24 million km<sup>2</sup>). Each of these articles employed extensive scene normalization procedures as a part of their preprocessing. Reiner et al. (2023) further



**Fig. 4.** Temporal characteristics of PlanetScope datasets for articles in the review list which use time series data. Total length of time series is the number of days between the first date in the time series and the last date in the time series, average revisit time is the average number of days between images in the time series, and image days refers to the number of individual dates in the time series where PlanetScope imagery was acquired. The top panel shows temporal characteristics for all articles, while the bottom panel is zoomed in to show articles with revisit time less than 120 days.

addressed the challenge of processing such a vast dataset by dividing their workflow into 1-degree tiles.

While the majority of articles use PlanetScope at its native spatial resolution (3–4.77 m depending on the data product; Table 2), it is resampled to different spatial resolutions in 23 articles. Many articles find that models have greater performance when developed using finer spatial resolution data. For mapping tree cover across Africa, Reiner et al. (2023) used 3 m PlanetScope data for mapping forests but resampled the data to 1 m to improve accuracy when detecting trees outside of forest stands. Song et al. (2024) found that 3 m PlanetScope data was better than data which had been resampled to between 6 and 30 m for estimating stand composition at 5 sites in the neotropics. Contrary to others, Shimizu et al. (2020) found that PlanetScope data resampled to lower resolutions produced more accurate models of canopy height. For predicting bird species richness, Silveira et al. (2023) found a non-linear relationship between spatial resolution and model performance, with the best results obtained using 3 m PlanetScope data; substantially worse results obtained at resolutions of 5, 10, and 30 m; and intermediate model performance when the data was resampled to 250 m. For predicting tree species diversity, Liu et al. (2024) also found a nonlinear relationship between spatial resolution and model performance—that prediction accuracy increased as PlanetScope data was resampled to 15 m then decreased in accuracy at coarser resolutions. This study also tested whether the choice of resampling method (nearest neighbor, bilinear interpolation, and cubic convolution) had an impact on the spectral responses of PlanetScope spectral bands and the subsequent vegetation indices calculated thereof; they concluded that the

choice of method did not significantly impact their results.

#### 4.3.3. Data products used

Of the reviewed articles which report the PlanetScope data products used, the vast majority used Analytic Scene (level 3B) or Tile (level 3A) products which are orthorectified and display surface reflectance (Table 1). These products are available with a 3 m pixel size and potential daily revisit, therefore fully leveraging the potential spatial and temporal resolutions of the PlanetScope constellation. On the other hand, eleven articles report using Analytic Basemap data products, which represent composites of monthly or quarterly PlanetScope time series. With a pixel size of 4.77 m and longer revisit, these products sacrifice spatial and temporal resolution for improved data quality. Although their higher levels of cross-calibration make them suitable for monitoring large areas, only three articles use basemap products to study areas larger than a single PlanetScope scene (Pacheco-Prado et al., 2024; Takasaki et al., 2022; Z. Wang et al., 2024), with several others instead leveraging the basemaps' data quality for monitoring time series (Lucanus et al., 2021; Pascual et al., 2022; Picoli and Helsen, 2024; Ping et al., 2023; Reiche et al., 2021; Welsink et al., 2023). However, Planet's workflow for producing basemaps from scene products was adapted in several publications in order to conduct monitoring at national and continental scales (Csillik et al., 2019; Csillik et al., 2020; Csillik and Asner, 2020a, 2020b; Reiner et al., 2023). Two articles report using Basic Scene products which display top-of-atmosphere radiance and have no geometric correction: Gašparović et al. (2018b) used a DEM to manually orthorectify Basic Scenes prior to fusing them with Sentinel-2;

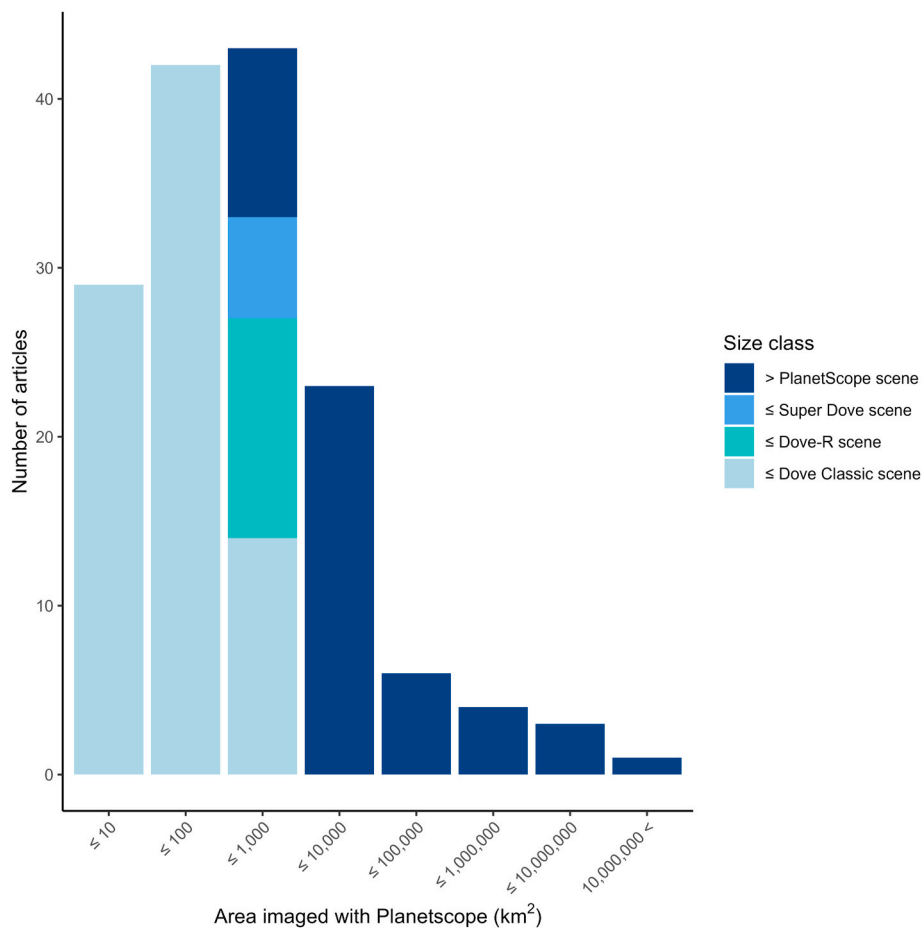


Fig. 5. Histogram of spatial areas imaged using PlanetScope in articles in the review list. The colours indicate the size of areas relative to the size of a single PlanetScope scene. A single Dove Classic scene is 192 km<sup>2</sup>, a Dove-R scene is 384 km<sup>2</sup>, and a Super Dove scene is 637 km<sup>2</sup>.

in a subsequent article, these fused images were used to detect urban vegetation in Zagreb (Gasparović et al., 2018a). In addition, two articles used Visual products which are optimized for visual inspection and consist of RGB bands. Although these products are not intended for analytic purposes, they have been used to achieve relatively good results. For monitoring forest harvesting in Italy, Francini et al. (2020) applied a novel change detection algorithm to a time series of Visual Ortho Scenes and obtained a producer's accuracy of 92 % and user's accuracy of 86 %. For mapping forest area across all of California, Carter et al. (2024a) applied a U-Net convolutional neural network to Visual basemaps and achieved an overall accuracy of 95 %.

#### 4.4. Data quality

PlanetScope imagery undergoes a series of pre-processing steps prior to distribution, with the highest levels of pre-processing being reserved for the basemap and Ortho Scene data products that are used in the vast majority of articles in this review (Planet Labs, 2024a, Table 2). Several articles (e.g. Mawlidan et al., 2024) invoke the atmospheric, radiometric, and geometric pre-processing provided by Planet as justification for not performing this pre-processing on their own. Nonetheless, many users of PlanetScope have reported issues with data quality, especially in the early days of the constellation. As a result, PlanetScope's data quality is a topic of perennial interest, with new articles frequently being published on the subject (e.g. Aragon et al., 2023; Dias et al., 2024; Frazier and Hemingway, 2021; Houborg and McCabe, 2018; Leach et al., 2019; Wang et al., 2021).

Amongst publications where data quality issues are reported, several steps are usually taken to exclude undesirable images. First, in the

process of gathering data for an analysis, metadata filtering is usually used to restrict results to “standard quality” images (i.e. those with sun altitude greater than or equal to 10°, view angle less than 20° from nadir, and fewer than 20 % saturated pixels; Planet Labs, 2024a); many users also filter by additional criteria including cloud cover, sun angle, acquisition date, or a host of other attributes (see Planet Labs (2023a) for a full list). Following filtering, many users manually inspect the data and remove or mask scenes where the quality is still deemed to be insufficient. While this two-step process is simple and robust—and is therefore the only quality control completed in the majority of articles in this review—users may find it insufficient if a very large number of images are to be used, or if it is necessary to include low quality images. For cases such as these, a variety of additional pre-processing techniques have been developed for improving the quality of PlanetScope data.

The purpose of this section is to provide a discussion of three issues with PlanetScope data quality as well as methods for improvement: radiometric inconsistency, geometric inconsistency, and the presence of noisy pixels. These three issues were selected because they were mentioned by articles in this review; for a more comprehensive discussion of potential issues with PlanetScope data quality, the reader should refer to Planet's quarterly L1 Data Quality Reports for the PlanetScope constellation<sup>1</sup> or L2 Data Quality Reports for PlanetScope surface reflectance products.<sup>2</sup>

<sup>1</sup> <https://support.planet.com/hc/en-us/articles/360037649554-L1-Data-Quality-Reports-for-the-PlanetScope-Constellation>.

<sup>2</sup> <https://support.planet.com/hc/en-us/articles/360037649614-L2-Data-Quality-Reports-for-the-PlanetScope-Constellation>.

#### 4.4.1. Radiometric inconsistency

Unlike other satellites such as Landsat or Sentinel-2, PlanetScope satellites do not contain on-board mechanisms for radiometric calibration (Collison et al., 2022). Instead, calibration of PlanetScope sensors is completed using near-coincident Sentinel-2 data (previously Landsat-8 and RapidEye), pseudo-invariant calibration sites, and daily images of the moon (Collison et al., 2022). These data are used to develop per-satellite models for radiometric calibration; for Ortho Scene surface reflectance products, Planet also offers optional per-scene corrections (widely used by articles in this review) using near-coincident Sentinel-2 data (Kington and Collison, 2022). Nonetheless, inconsistent radiometric quality is the most widely reported and discussed issue with PlanetScope data among articles in this review.

Radiometric inconsistencies arise from the fact that the same multispectral bands in different generations of PlanetScope sensors (i.e. Dove Classic, Dove-R, and Super Dove) detect slightly different ranges of the electromagnetic spectrum (Frazier and Hemingway, 2021, Table 1). Between sensors of the same generation, radiometric inconsistencies are caused by differences in orbital characteristics, hardware, and illumination conditions (Frazier and Hemingway, 2021). To mitigate these potential inconsistencies, analysis can be restricted to images from a single generation of PlanetScope sensor (Frazier and Hemingway, 2021). This strategy was explicitly employed by Petri et al. (2022), who state that they exclusively used data acquired by the Dove Classic satellites in order to maintain consistent radiometric quality. Even if not mentioned, this strategy is implicitly followed by many other studies which only use data from a single generation of satellite, including all those which only use data acquired before March 2020 or after April 2022 (when data were exclusively acquired by either the Dove Classic or the Super Dove satellites respectively).

Twenty-six articles in the review list report using additional pre-processing to radiometrically normalize their data. While two articles do not describe their methods in detail (Aik and Ismail, 2020; Tandoc et al., 2019), the remainder describe methods which can be grouped into 3 basic approaches: relative radiometric correction, within-scene correction, and temporal smoothing (Table 4).

Relative radiometric correction (RCC)—the process of changing the reflectance values of an image based on the values in a reference image (Yuan and Elvidge, 1996)—is the most common approach to radiometric normalization. Of the articles reviewed, almost an equal number of studies used Landsat and MODIS imagery. Zhao et al. (2023) used a deep learning model to fuse Harmonized Landsat and Sentinel-2 imagery with MODIS, thereby producing a series of reference images with 30 m spatial resolution and daily revisit. Three articles do RCC exclusively using PlanetScope data by designating one scene to be the reference then correcting adjacent scenes using pixels in regions which overlap the

reference. The potential upside of using a reference image produced by a different remote sensing system is that the high radiometric consistency of systems such as Landsat and MODIS can be leveraged, while a potential upside of using a PlanetScope reference is reduced computational requirements since no additional images are required for processing. The specific RCC procedure used by most articles is a histogram matching method pioneered by Wang et al. (2020) which consists of resampling a PlanetScope scene to match the spatial resolution of a MODIS reference image, matching the histograms of each PlanetScope band to each MODIS band separately, then applying the coefficients used to do this to PlanetScope imagery in its original resolution. This specific workflow is used by five additional articles (Song et al., 2024; J. Wang et al., 2024, 2023; Wu et al., 2021; Zhao et al., 2022).

The other two approaches to image normalization are collectively used by five articles in this review. Within-scene correction is the process of changing the reflectance values of a scene without using a reference image. Santiago et al. (2021) used two separate within-scene techniques by first applying a spatial smoothing filter over scenes then calculating the z-score for each band, while Francini et al. (2020) used a softmax function to normalize data in a dense time series. The third approach is temporal smoothing, where differences between sensors are mitigated by using a dense time series of overlapping images to calculate an indicator of central tendency for each pixel. For example, Dalponte et al. (2022) calculated mean pixel values based on a month-long time series of PlanetScope scenes while Dixon et al. (2021) used median pixel values based on a 19-day moving window.

To date, few comparison studies have been undertaken to assess the relative effectiveness of different radiometric normalization methods. Wegmueller and Townsend (2021) used an RCC method based on LOESS regression and a PlanetScope reference and found it produced improved results when compared with adjustment by ordinary least squares regression. Zhao et al. (2023) found superior results using histogram matching by using fused Landsat, Sentinel-2, and MODIS data for the reference image versus MODIS alone. While many articles find that additional radiometric normalization procedures either reduce noise or improve model performance (Leach et al., 2019; Wang et al., 2020; Wu et al., 2021; Zhao et al., 2023), Shimizu et al. (2020) refrained from engaging in radiometric normalization after testing the radiometric consistency of their data and finding it adequate. In developing a workflow for automatically detecting forest fires, Rodríguez-Esparragón et al. (2024a) state that they intentionally did not use additional radiometric correction in order to develop a technique that was both simple and robust; after testing numerous features, they found that NDVI, WDRVI, and YNDVI were relatively insensitive to radiometric inconsistencies in the data.

**Table 4**

Overview of additional radiometric correction techniques employed by articles in the review list. Reference image data are indicated for relative radiometric correction.

Approach	Method	Articles
Relative radiometric correction	Linear function	Landsat: (Csillik et al., 2019; Csillik et al., 2020; Csillik and Asner, 2020b; Csillik and Asner, 2020a) PlanetScope: (Miura et al., 2023; Dalponte et al., 2020)
	Orthogonal regression using invariant pixels	Landsat: (Leach et al., 2019; Keay et al., 2022)
	LOESS regression	PlanetScope: (Wegmueller and Townsend, 2021)
	Histogram matching	Landsat: (Reiner et al., 2023) MODIS: (Wang et al., 2020; J. Wang et al., 2023; J. Wang et al., 2024; Wu et al., 2021; Zhao et al., 2022; Song et al., 2024), Combined Landsat/MODIS/Sentinel-2: (Zhao et al., 2023) PlanetScope: (Aquino et al., 2024)
Within-scene correction	Softmax function	Francini et al. (2020)
	Gaussian kernel, Z-score	Santiago et al. (2021)
Temporal smoothing	Monthly mean	Dalponte et al. (2022)
	19-day moving window median	Dixon et al. (2021)
	Weekly mean	Falanga et al. (2024)
	10-day median	Zabeo et al. (2024)

#### 4.4.2. Noisy pixels

In order to accurately monitor vegetation and forests, it is usually necessary to exclude or correct pixels with ephemeral noise that may interfere with the underlying signal. Although data corruption or issues with PlanetScope hardware have sometimes been known to introduce noise (Bahoul et al., 2024), no reviewed articles report such problems. On the other hand, multiple articles report noisy pixels related to errors with Planet's UDM assets, the quality control layers that are published to assist users with differentiating between clear pixels and those which contain cloud, haze, shadow, and snow. UDMs are available for almost all scene imagery starting in 2018, and improved iterations have been introduced over time (Planet Labs, 2023a, 2024a). For the latest iteration—UDM2.1, introduced in November 2023—the precision (user's accuracy) for differentiating clear pixels from noisy pixels was 0.871 (Planet Labs, 2023a), indicating that a non-trivial amount of noisy pixels may remain in imagery even after masking with the UDM. To mitigate this issue, twelve articles in this review describe the use of pre-processing techniques other than the UDM to automatically remove noisy pixels from PlanetScope data.

In the simplest cases, noisy pixels are identified and masked in individual images using a threshold value for spectral features such as the Dove bands (Francini et al., 2020; Pan et al., 2024; Rösch et al., 2022), GNDVI (Dixon et al., 2021), or the principal components of Dove bands (Wang et al., 2020). This approach leverages the fact that noisy pixels, such as those containing cloud and snow, often have brightness values in optical imagery which are well outside the normal range of the underlying land surface (Dozier, 1989). In cases where the noise is more subtle, such as smoke or haze, it may be advantageous to use multi-temporal data for detection. Using a despiking algorithm adapted from Kennedy et al. (2010), Leach et al. (2019) calculated the difference between observed PlanetScope NDVI values at a given time point and predicted values interpolated from previous and subsequent time points then classified all anomalies exceeding a certain threshold as noise; this same technique was later used by Keay et al. (2022) and (Pan et al., 2024). Several articles combine information from both unitemporal and multitemporal data to identify noise. For instance, Shimizu et al. (2020) used a version of the Automatic Time-Series Analysis algorithm (ATSA; Zhu and Helmer, 2018) to mask cloud and cloud shadow by i) identifying clouds with a k-means applied to individual HOT index images, ii) refining these predictions by identifying outliers in a HOT timeseries, iii) identifying candidate cloud shadow pixels using cloud height and sun angle geometry, and iv) refining these predictions by identifying outliers in a Shadow index timeseries. In its original formulation, ATSA was developed for use by sensors with shortwave infrared bands to calculate the Shadow index and thermal bands for assessing cloud height, although Zhu and Helmer (2018) suggest several work-arounds for cases when these bands are unavailable. For explicit use with PlanetScope's RGB-NIR bands, Wang et al. (2021) developed a similar algorithm to ATSA called the SpatioTemporal approach for Automatic Cloud and Shadow Screening (STI-ACSS). When tested over 6 tropical sites, STI-ACSS achieved a mean overall accuracy of 98 % for detecting clouds and cloud shadows; by comparison, Planet's UDM2 asset achieved a mean accuracy of 87 %, while other popular noise masking algorithms including ATSA, Fmask, and IHOT scored lower (Wang et al., 2021). As a result of its success, STI-ACSS has appeared in several other articles (Song et al., 2024; J. Wang et al., 2024, 2023; Wang et al., 2022).

#### 4.4.3. Geometric inconsistency

Although several sources (e.g. Frazier and Hemingway, 2021; Houborg and McCabe, 2018) have commented on the low geometric quality of PlanetScope data, this aspect of image quality is mentioned by few articles in this review. In 2022, Planet introduced a new tool for co-registering overlapping scenes as a part of its Orders API<sup>3</sup>; however,

only one article in this review reports using it (Falanga et al., 2024). Three articles (Dixon et al., 2021; Leach et al., 2019; Wegmueller and Townsend, 2021) mention assessing the geometric quality of their data and finding it adequate. On the other hand, nine articles mention applying additional geometric corrections to PlanetScope data. Four of these do not specify the method used (Aquino et al., 2024; Francini et al., 2020; Gašparović et al., 2018a; Neyns et al., 2023), while three use proprietary software such as ENVI (Ye et al., 2021, 2022) and ArcGIS (Tandoc et al., 2019). To georeference a single PlanetScope scene, Stoll et al. (2022) report achieving an accuracy of <4 m using ground control points that were collected during field surveys. For automatically co-registering a dense timeseries of PlanetScope data Keay et al. (2022) used the AROSICS algorithm, which is able to detect sub-pixel geometric differences between images using phase correlation; with this method, they report achieving registration accuracy of less than 1 pixel (<3 m).

#### 4.5. PlanetScope features

##### 4.5.1. Spectral bands and indices

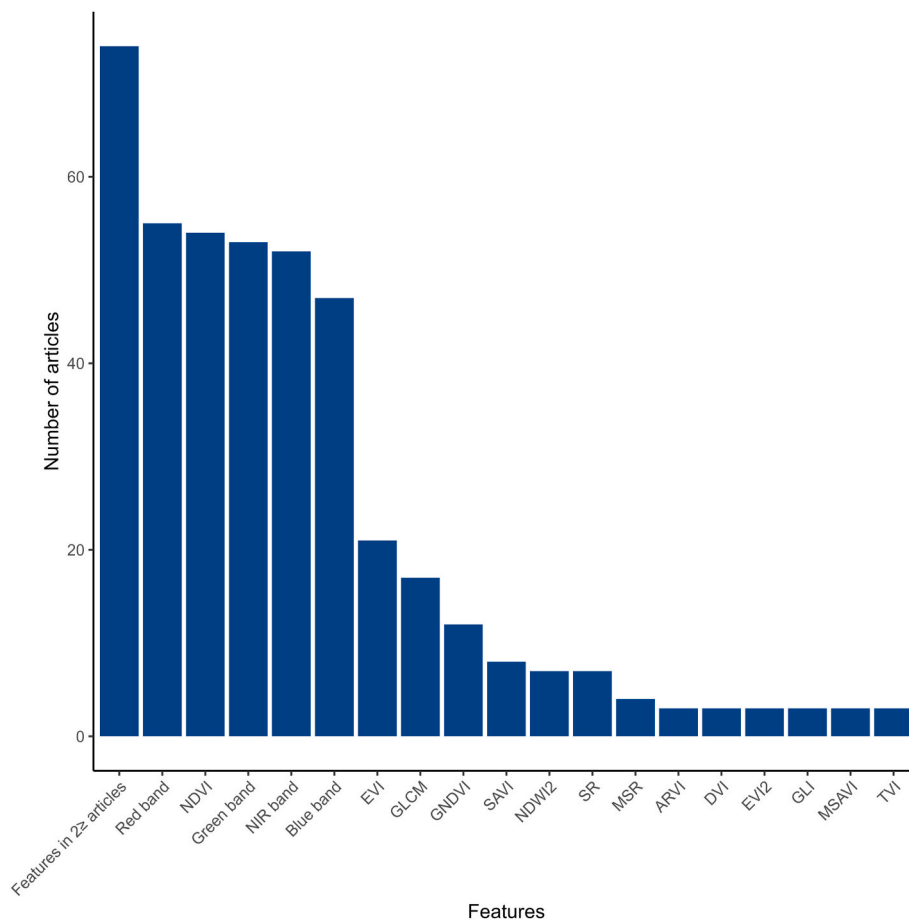
A wide array of spectral features (features based on the surface reflectance of sensor bands or algebraic transformations thereof) were used by articles in the review list to train predictive models, with the majority of these appearing in two or fewer articles (Fig. 6). The Dove sensor bands appear the most, with the NIR, red, and green bands being used more frequently than the blue band. Csillik and Asner (2020b) intentionally excluded the blue band from their analysis of aboveground carbon in Peru, citing susceptibility to atmospheric noise as their reason for doing so. Most of the important vegetation indices are calculated using the NIR and red bands. The Normalized Difference Vegetation Index (NDVI) is the most-used vegetation index, and appears in almost as many articles as the red, NIR, and green bands. With the exception of the Simple Ratio Index (SR), the remaining vegetation indices are all ratio indices which are adapted from or similar in form to NDVI.

Although 8-band PlanetScope data has been available since 2020, analysis approaches are primarily based on the four core multispectral bands which are common to each generation of satellite: blue, green, red, and near-infrared. Only twelve articles in the review—all published in 2023 or 2024—have used the four additional spectral bands provided by the Super Dove satellites; however, several of these have found their use advantageous. For instance, Galvão et al. (2023) found that vegetation indices which incorporated the green I and red edge bands were less sensitive than EVI to noise caused by sun angle for characterizing vegetation phenology in the Amazon rainforest. Using the Boruta algorithm for feature selection (Kursa et al., 2010), Matiza et al. (2024a) determined that the yellow and red edge bands—as well as derivative indices and textures—were important for modelling aboveground biomass in South Africa. In the only article to explicitly compare 4-band and 8-band PlanetScope data, Basheer et al. (2024a) found that using 8-band data resulted in 5–20 % higher user's accuracy when compared with 4-band data for identifying forest cover in urban areas. On the other hand, Njomaba et al. (2024) found that Super Dove bands did not improve predictions of tree species diversity in Ghana. Uptake of 8-band data has also spurred the development of novel vegetation indices. Rodríguez-Esparragón et al. (2024b) introduced the Yellow Normalized Difference Vegetation Index (YNDVI), which they found was effective for distinguishing between healthy vegetation, unhealthy vegetation, and soil in the Canary Islands. In a subsequent article (Rodríguez-Esparragón et al., 2024a), YNDVI was found to be highly effective for mapping burnt areas.

##### 4.5.2. Texture variables

A wide variety of derivative variables have been calculated from PlanetScope bands and vegetation indices. An important group include image texture which are calculated from groups of adjacent pixels, and appear in 19 articles. The most common type of textures—used in 17 articles—are those based on the Grey Level Co-occurrence Matrix

<sup>3</sup> <https://docs.planet.com/develop/apis/orders/tools/#coregister>.



**Fig. 6.** The number of articles in the review list which use different PlanetScope features for training a predictive model. NDVI: Normalized Difference Vegetation Index (Huang et al., 2020); EVI: Enhanced Vegetation Index (Huete et al., 1994); GLCM: Grey Level Co-Occurrence Matrix (Haralick et al., 1973); GNDVI: Green Normalized Difference Vegetation Index (Gitelson et al., 1996); SAVI: Soil Adjusted Vegetation Index (Huete, 1988); SR: Simple Ratio (Jordan, 1969); NDWI2: Normalized Difference Water Index (McFeeters, 1996); TVI: Transformed Vegetation Index (Rouse, 1974); MSAVI: Modified Soil Adjusted Vegetation Index (Qi et al., 1994); GLI: Green Leaf Index (Gobron et al., 2000).

(GLCM), which are produced by generating a matrix for the frequency with which pixels of different brightness values occur next to each other and then calculating summary statistics based on that matrix (Hall-Beyer, 2017; Haralick et al., 1973). GLCM metrics based on PlanetScope data have principally been used in applications related to forest inventory such as tree mapping (Cui et al., 2022; Jin et al., 2021), modelling aboveground biomass (Madundo et al., 2023), and tree species identification (Liu et al., 2024; Ziegelmaier Neto et al., 2024); they are also used for detecting and characterizing different forest disturbances (Cho et al., 2023; Nasiri et al., 2023). The majority of articles which feature GLCM textures report calculating them using a  $3 \times 3$  pixel moving window (the smallest size possible), although several articles have tested the results of using other window sizes as well. For example, Rösch et al. (2022) found that a window size of  $29 \times 29$  pixels was optimal for classifying tree species in Italy, while Pinagé et al. (2023) used a window size of 180 pixels for classifying degraded forest in the Amazon. The visible and NIR bands are the spectral features which are most frequently used for calculating GLCM textures, although vegetation indices which incorporate the NIR band are also commonly used. In a comparison of seven different types of spatial and spectral heterogeneity metrics for assessing tree species diversity in Germany, Liu et al. (2024) found that GLCM texture metrics calculated from MSAVI, NIR, red, and green—as well as Rao's Q (Rocchini et al., 2017) calculated from NIR—were the most important predictors. Two articles also use texture features produced through Fourier-Based Textural Ordination (FOTO; Coutron et al., 2006). Csillik et al. (2020) used FOTO features

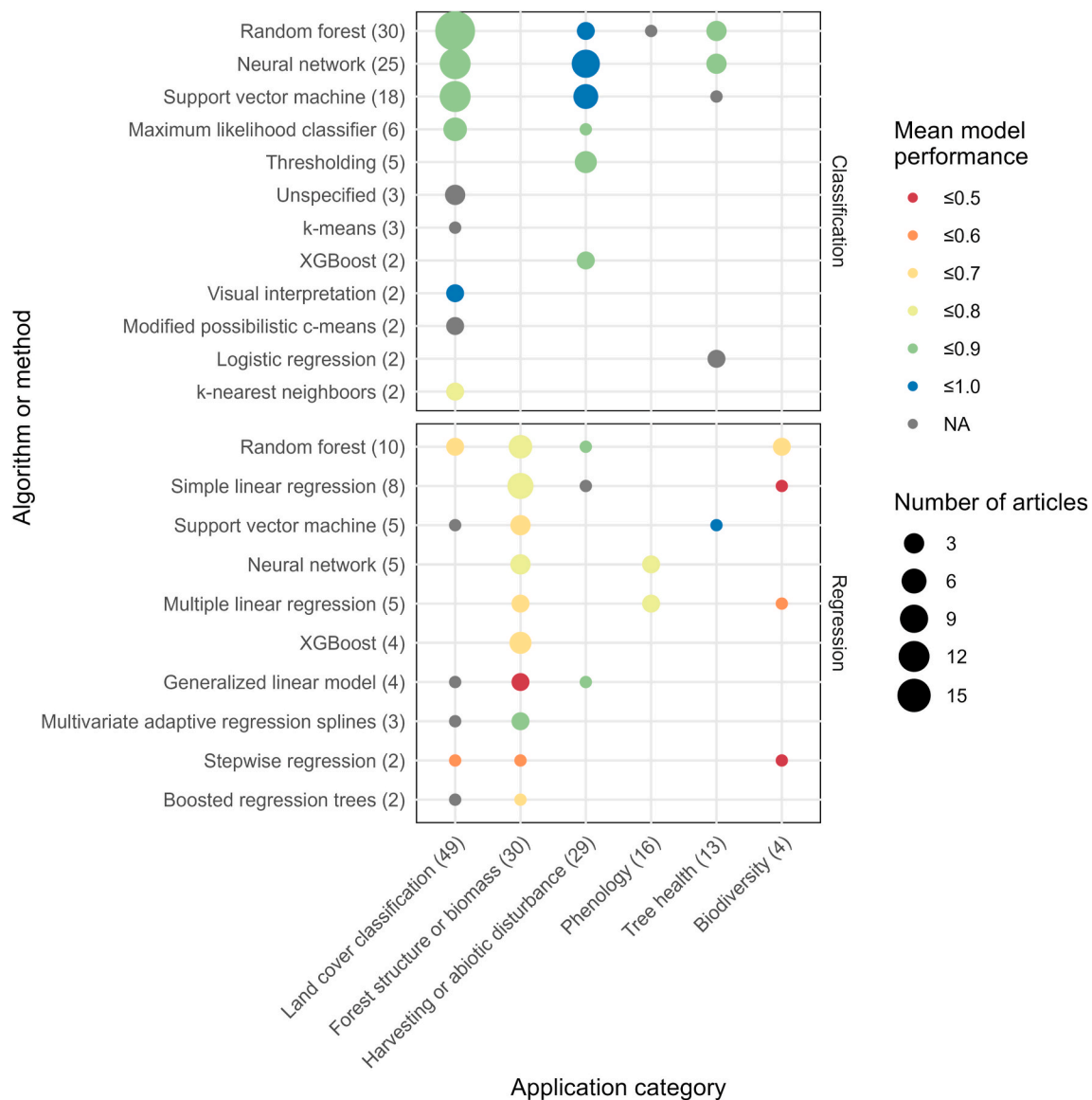
to model canopy height across Peru, while Migolet and Goïta (2020) used them for estimating aboveground biomass at an oil palm plantation in the Congo basin.

#### 4.6. Modelling approaches

A diverse array of methods have been used to analyze PlanetScope data (Fig. 7). Typically, these consist of applying a statistical or machine learning algorithm in order to develop a classification or regression model to predict a phenomenon using variables derived from PlanetScope.

##### 4.6.1. Classification

Seventy-eight articles use a classification-based approach to model or map phenomena in forested landscapes with PlanetScope data. The most popular family of classification algorithms consists of ensemble methods based on decision trees, including random forest, XGBoost, and AdaBoost. In particular, random forest is the most widely used algorithm, mostly being used for identifying forested areas or trees, although identifying tree species and forest types has also been a major application. Besides random forest, the other most frequently used classification models are neural networks for deep learning, which appear in 25 articles. The most popular architecture is U-Net, a modified convolutional neural network which can produce accurate classification and segmentation even with relatively limited training data (Ronneberger et al., 2015). Neural networks have also been used for identifying areas that



**Fig. 7.** Classification and regression algorithms used for different applications by at least 2 articles in this review. The size of the points within the plot area indicates the number of articles for each combination of algorithm and application, while the numbers in brackets on the axis labels indicate the total articles for each category. Individual articles may be counted across multiple applications or algorithms. Papers where PlanetScope is only used for validation are not counted. The color of points indicates the mean model performance (overall accuracy expressed as a proportion for classification or coefficient of determination for regression).

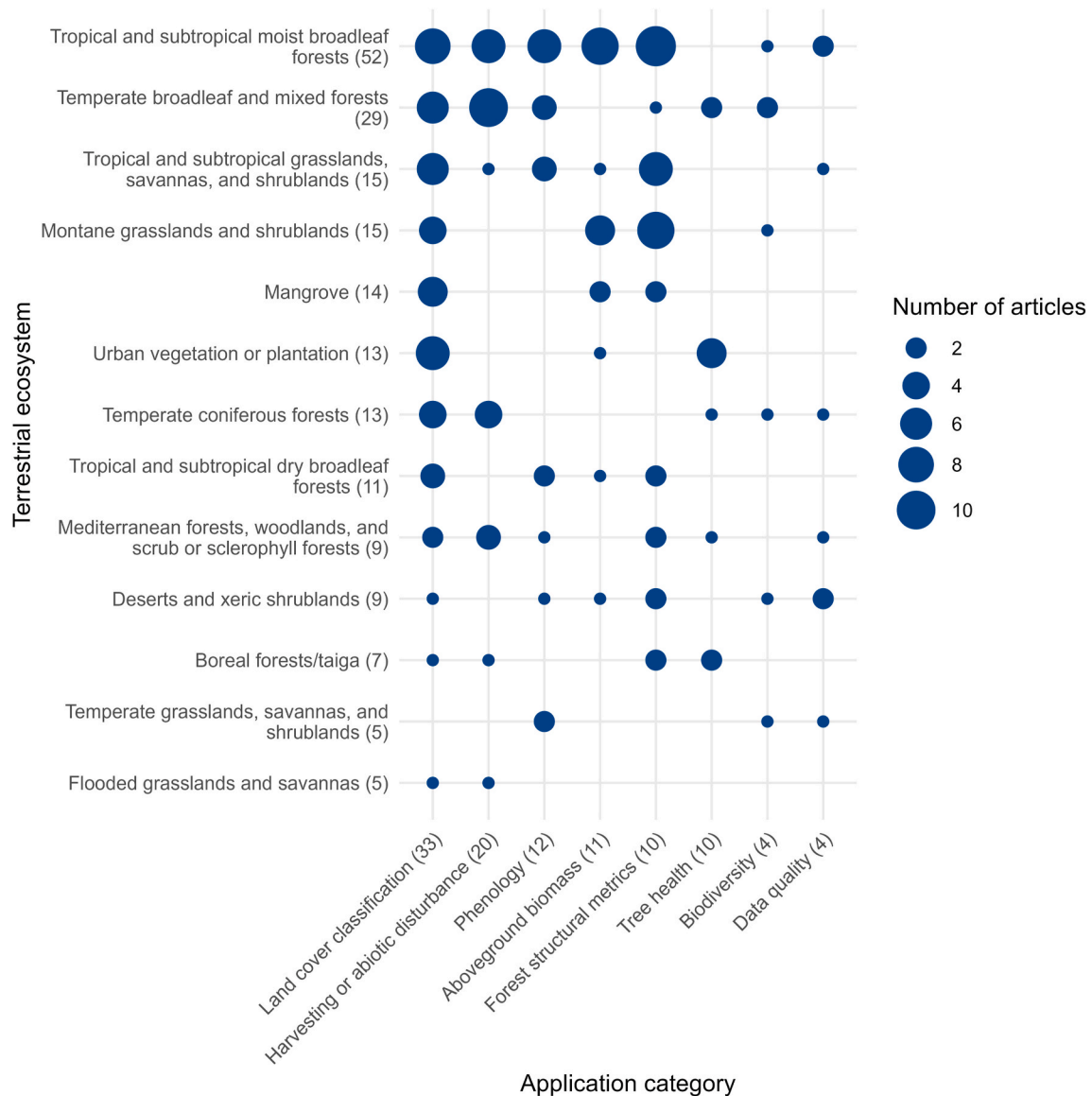
have been disturbed by fire—for example, in South Korea (Cho et al., 2023; Widya and Lee, 2024), Algeria (Zikiou et al., 2024), Brazil (Gonçalves et al., 2023), and California (Carter et al., 2024; Dixon et al., 2023). Support vector machines are the algorithm which has been used in the third most articles, appearing in 18. Such algorithms are mostly used in articles where their performance for classification is contrasted with other methods (Basheer et al., 2024b; Cui et al., 2022; Iqbal et al., 2023; Kluczek et al., 2023). The accuracy of classification models tends to be high, with the average accuracy for most applications and algorithms exceeding 80 % (Fig. 7). In articles where different methods are directly compared, the random forest algorithm tends to produce the highest classification accuracies, although the difference in accuracies between it and neural networks or support vector machines tend to be minor.

Of the articles that feature land cover classification, 19 % use an object-based approach. Of that, a small number directly compare object-based and pixel-based methods and those that do report favorable results from object-based analysis. Mapping rubber plantations in

northern China, Cui et al. (2022) found that using multiresolution segmentation prior to random forest classification increased overall accuracy from 90 % to 94 %; the results were more moderate when the same comparison was made with support vector machines. For detecting forest harvesting, Nasiri et al. (2023) found that applying the random forest algorithm to objects produced via multiresolution segmentation increased overall accuracy from 98 % to 99 % when compared with pixel-based analysis. While similar findings were obtained for classification using support vector machines, they found that pixel-based analysis was more accurate when classification was done using a neural network. Also to detect forest harvesting, Mawlihan et al. (2024) found that object based image analysis using the mean shift algorithm in ArcGIS Pro resulted in higher accuracy than pixel-based maximum likelihood classification (89 % versus 82 %) but lower accuracy than pixel-based classification using support vector machines (92 %).

#### 4.6.2. Regression

Forty-one articles apply regression-based approaches to model



**Fig. 8.** Number of articles focused on each application within different ecosystem types. The size of the points within the plot corresponds to the number of articles, while the numbers in brackets on the axis labels indicate the total articles for each category. Individual articles may be counted across multiple applications or ecosystems. Except for “Urban vegetation and plantation,” all terrestrial ecosystems correspond to the biomes described in [Olson et al. \(2001\)](#).

continuous phenomena using PlanetScope data. These articles predominantly employ machine learning algorithms such as ensemble tree-based methods, neural networks, and support vector machines in lieu of more traditional statistical regression models ([Fig. 7](#)). One possible explanation for the popularity of these machine learning algorithms is that they make few assumptions about the underlying statistical properties of the data, and therefore may be applied in a wide range of contexts ([Holloway and Mengersen, 2018](#); [Pichler and Hartig, 2023](#)).

Predicting aboveground biomass has been the main use of regression algorithms applied to PlanetScope data ([Fig. 7](#)). For this purpose, the best average results have been achieved using multivariate adaptive regression splines (MARS; [Baloloy et al., 2018](#); [Migolet and Goita, 2020](#)), while random forest and XGBoost also consistently produce superior results in articles that compare multiple methods. Model performance tends to vary widely between different algorithms and different contexts. Among the most accurate, [Matiza et al. \(2024b\)](#) achieved an  $R^2$  of 0.82 when using XGBoost to predict aboveground biomass in a reforested area with a combination of PlanetScope spectral features and ancillary variables. Likewise, [Migolet and Goita \(2020\)](#) achieved  $R^2$

values of 0.82 and 0.81 by applying MARS and multiple linear regression to predict aboveground biomass using texture metrics in an oil palm plantation. Among the least accurate, [Madundo et al. \(2023\)](#) achieved  $R^2$  values of 0.08 and 0.16 using generalized additive models and XGBoost for predicting aboveground biomass in a Tanzanian forest. For predicting mangrove biomass in a plantation in Vietnam, [Huong et al., \(2023\)](#) reported a wide range of results, achieving  $R^2$  values of 0.21 and 0.17 using a generalized linear model and generalized exponential model and values over 0.70 using support vector machines and random forests. These examples highlight the potential strength of using algorithms which are both non-parametric and flexible enough to fit non-linear relationships between variables.

#### 4.7. Applications

PlanetScope data has been used for a wide variety of forest monitoring applications ([Fig. 8](#)), which can be organized into eight broad categories based on subject matter. The purpose of this section is to provide an overview of the breadth of forest-related subject matter that

PlanetScope has been used to research, including the types of analytic approaches used.

#### 4.7.1. Land cover classification

Of the 129 articles reviewed which analyzed PlanetScope data rather than using it for visual validation, 48 (37 %) use PlanetScope data for general land cover classification such as mapping forested area (e.g. [García-Ontiyuelo et al., 2024](#); [Maung et al., 2023](#)), differentiating between different types of forest (e.g., [Ye et al., 2021](#)), or determining tree species (e.g., [Kluczek et al., 2023](#)). The most typical approach is to apply a supervised classification algorithm to unitemporal data; however, classifications have also been enhanced by incorporating phenological information through the use of image time series ([Cui et al., 2022](#); [Ferla et al., 2023](#); [Ye et al., 2022](#)). In the vast majority of cases, the analytic approach used is based on “hard” classification (i.e. a PlanetScope pixel is assigned to a single class); however, there is a small but growing body of work in which fuzzy classification (i.e. the belongingness of pixels to multiple classes is assessed) is applied to PlanetScope data, specifically for mapping individual tree species ([Mehrotra et al., 2022, 2023, 2024](#)).

#### 4.7.2. Harvesting or severe abiotic disturbance

Twenty-six articles use PlanetScope data for monitoring harvesting (e.g., [Mawlidan et al., 2024](#)) or severe abiotic disturbances such as fires (e.g., [Gonçalves et al., 2023](#)), wind (e.g., [Dalponte et al., 2020](#)), and landslides ([Furukawa et al., 2020](#)). In the majority of articles, the goal is to map disturbed areas using bitemporal data acquired before and after the disturbance, although several articles feature attempts to map disturbed areas with unitemporal data (e.g., [Deigele et al., 2020](#)) or by applying change detection algorithms to dense time series of data ([Francini et al., 2020](#); [Keay et al., 2022](#)). Virtually all articles use a classification approach, with the type of approach tending to vary depending on how timeseries data are used: supervised classification is predominantly used with unitemporal data, while a mixture of supervised and unsupervised algorithms are used with time series data. While most articles focus on mapping the disturbed area, several also assess the severity of disturbances using the magnitude of the change in PlanetScope features between points in time ([Michael et al., 2018](#); [Wegmueller and Townsend, 2021](#); [Zikiou et al., 2024](#)).

#### 4.7.3. Forest structure or biomass

Twenty-three articles use PlanetScope for assessing aboveground biomass or carbon (e.g. [Csillik and Asner, 2020a](#)), or for estimating a variety of forest structural attributes such as canopy height (e.g., [Shimizu et al., 2020](#)), canopy cover (e.g., [Loranty et al., 2018](#)), and stem density ([Mulatu et al., 2019](#)). Invariably, regression-based approaches are used to model these attributes as continuous variables. While the goal of most articles is to test the potential of PlanetScope for predicting forest structure or biomass, two articles follow an inferential approach to assess the impact of understory vegetation on estimates of forest cover ([Bendavid et al., 2023](#); [Loranty et al., 2018](#)). Many articles use field data for validation; in these cases, PlanetScope data are often aggregated according to the geometry of the sampling plots, which are usually larger than a single PlanetScope pixel ([Baloloy et al., 2018](#); [Migolet and Goïta, 2020](#); [Mulatu et al., 2019](#)). However, maps are also produced at finer resolutions by using indices of forest structure based on other high-resolution remote sensing data—in particular, aerial lidar—for validation (e.g., [Gyawali et al., 2024](#); [Shimizu et al., 2020](#)).

#### 4.7.4. Phenology

Fifteen articles use PlanetScope data to study forest phenology. For the most part, these articles apply regression models to dense time series in order to assess the timing of phenological events such as budburst (e.g., [Zhao et al., 2023](#)) or general flowering ([Dixon et al., 2021](#); [Miura et al., 2023](#)). Two articles also use PlanetScope data in order to evaluate the influence of solar illumination conditions for assessing tropical forest phenology ([Galvão et al., 2023](#); [Petri et al., 2022](#)).

#### 4.7.5. Tree health

Thirteen articles investigate topics related to tree health, including diseases (e.g., [Guo et al., 2021](#)), damage by insects or wildlife (e.g., [Trubin et al., 2023](#)), tree mortality ([Dixon et al., 2023](#)), and drought stress ([Pascual et al., 2022](#)). Similar to the articles that use PlanetScope for monitoring harvesting and abiotic disturbances, the majority of articles associated with tree health apply supervised classification to unitemporal or bitemporal data. Unlike the articles on harvesting and abiotic disturbances, many articles on tree health conduct monitoring at the scale of individual tree crowns (ITCs; e.g., [Dalponte et al., 2022](#)) instead of pixel or area-based approaches.

#### 4.7.6. Biodiversity

Only four articles used PlanetScope data to predict biodiversity. Three of these are concerned with tree species diversity ([Gyamfi-Ampadu et al., 2021](#); [Liu et al., 2024](#); [Njomaba et al., 2024](#)), while one is concerned with bird species ([Silveira et al., 2023](#)). In each article, regression models are developed to predict a diversity metric such as Shannon’s diversity index or species richness.

#### 4.7.7. Data quality

There are also five articles where the main subject is assessing or improving PlanetScope data quality in forested landscapes. [Johnson et al. \(2018\)](#) used k-means clustering to compare the radiometric quality of PlanetScope data with Landsat-8. [J. Wang et al. \(2021\)](#) developed a procedure for masking clouds and shadows which achieved higher accuracy than Planet’s own UDM product; a subsequent article followed up on this work by presenting a novel object-based method for filling gaps in PlanetScope time series ([Wang et al., 2022](#)). [Leach et al. \(2019\)](#) developed a method for improving the radiometric consistency of PlanetScope data by harmonizing PlanetScope bands with Landsat using orthogonal regression.

#### 4.8. Paradigms in PlanetScope research

The combination of high spatial resolution, high temporal resolution, and spatially exhaustive global coverage are qualities which potentially allow PlanetScope to be used in applications related to near-real time monitoring or precision forestry. The purpose of this section is to focus on research which explicitly attempts to leverage PlanetScope data for these purposes.

##### 4.8.1. Near-real time monitoring

The purpose of near-real time monitoring is to provide information about changes in the forest in as short a time as possible after they occur. Several articles develop frameworks for using time series of PlanetScope data to detect changes in near-real time. [Csillik and Asner \(2020b\)](#) used a combination of PlanetScope spectral indices and Sentinel-1 backscatter to predict changes in aboveground carbon density across Peru; however, their use of composite images meant that they were limited to detecting changes at monthly or quarterly timesteps. In contrast, most articles use daily scene products in order to maximize the temporal density of their time series. [Francini et al. \(2020\)](#) introduced the Thresholding Rewards and Penances algorithm for detecting forest harvesting on the west coast of Italy. According to this method, a forested pixel is given a score which is stored in a memory layer. When new data is acquired, the score is increased or decreased depending on whether or not the difference between the new pixel value and the time series median exceeds a given threshold. Pixels are classified as harvested if the score reaches a predefined target. By applying this method to a time series of images transformed with the Hue index ([Escadafal et al., 1994](#)) then normalized using the softmax function, they were able to detect harvesting with a user’s accuracy of 86 % and a producer’s accuracy of 92 %. [Keay et al. \(2022\)](#) also developed a workflow for detecting forest harvesting using a dense time series of PlanetScope scenes, this time in Ontario. First, the data was normalized using the method proposed by [Leach et al. \(2019\)](#),

NDVI was calculated, and the time series was denoised using a Savitzky-Golay filter. Next, the Kernelized Change Point Detection algorithm (Celisse et al., 2018) was used to generate a set of candidate breakpoints for each pixel. A final breakpoint was identified—and the pixel was classified as harvested—using a set of rules based on minimum threshold NDVI values and attributes of the time series segments which were separated by the breakpoint. Using this method, harvesting was detected with overall accuracies of 78–90 % and a temporal error 9–10 days.

The advantage of continuous monitoring using a time series is that it allows changes to be detected for which the precise timing is unknown. In cases where the timing of a potential change event is known (e.g. a storm or a fire) it may be possible to undertake near-real time monitoring using a shorter time series around when the event occurred. Many articles describe efforts to do this using bitemporal imagery acquired before and after the disturbance, often using methods which combine image differencing and clustering. For example, Wężyk et al. (2019) used two images acquired one day apart to evaluate hurricane damage in Poland. Each image was segmented into superpixels using the Simple Linear Iterative Clustering algorithm (SLIC; Achanta et al., 2010), an index of hurricane damage was calculated for each superpixel using pre and post-hurricane canopy height models, and a linear regression model was developed for predicting hurricane damage using NDVI and the four Dove bands, achieving an  $R^2$  of 0.83. This article is unique because PlanetScope images acquired one day apart were able to be used; in many cases, the severe weather that causes a disturbance may also be accompanied by heavy cloud cover which could inhibit data acquisition. Chung and Kim (2020) used two images acquired three days apart to map fire damage in South Korea. By generating superpixels using SLIC, applying DBSCAN to aggregate superpixels into larger objects, then evaluating the change in NDVI, they were able to achieve overall accuracies above 96 %. Wegmueller and Townsend (2021) presented a similar framework called ASTRAPE for using bitemporal imagery to swiftly assess damage from stand-replacing abiotic disturbances in the United States. This object-based semi-supervised approach consists of two modules: first, the k-means algorithm is used to segment images and the difference between the pre- and post-event images is calculated. Next, the unsupervised Jenks Natural Breaks and supervised XGBoost algorithms are used in tandem to predict a damage class for each object. This methodology was employed to map wind damage in Wisconsin (USA) using images acquired 12 days apart with an overall accuracy of 78 %, and hurricane damage in Louisiana (USA) using images acquired 40 days apart with an overall accuracy of 86 %. For mapping windthrow damage in northern Italy, Dalponte et al. (2020) applied unsupervised change vector analysis to normalized PlanetScope images acquired three weeks apart. They emphasize that accuracy was improved by using images that reflect similar phenological and illumination conditions.

Several articles have also experimented with using imagery taken from a single point in time to characterize forest disturbances. Compared to the bitemporal approach, methods based on a unitemporal approach only make use of a post-event image. Therefore, while methods for analyzing time series often incorporate image differencing, unitemporal methods depend on differences in the spectral or spatial characteristics of disturbed and undisturbed areas. Many articles which follow this approach have used deep learning for semantic segmentation. Deigele et al. (2020) achieved an intersection over union score (IoU; a metric commonly used to assess the accuracy of image segmentation, calculated by dividing the intersection of predicted and ground truth regions by their union (Rahman and Wang, 2016)) of 55 % by using U-Net for mapping windthrow in Bavaria. Also with U-Net, Cho et al. (2023) were able to map wildfire damage in Korea, achieving IoU scores above 79 % using imagery acquired in as little as three days post-disturbance. In a comparison of seven different convolutional neural network and transformer architectures for mapping burned areas in the Brazilian Pan et al. (2024) achieved IoU scores between 88 and 92 %. Deigele et al. (2020) highlight that a unitemporal approach may be beneficial for near-real

time monitoring by allowing for faster characterization of a disturbance than a multitemporal approach; however, potential trade-offs should be considered: for detecting heartwood rot in Norway spruce, Dalponte et al. (2022) found that using unitemporal imagery resulted in lower classification accuracy than using multitemporal imagery.

#### 4.8.2. Precision forest monitoring

**4.8.2.1. Individual tree crowns.** In many contexts, the spatial resolution of PlanetScope is sufficient for potentially conducting monitoring at the scale of an individual tree crown (ITC). In the majority of articles, ancillary data is first used to segment or identify ITCs prior to analysis with PlanetScope, with manual segmentation mostly being favored over algorithmic methods. In multiple articles, manual ITC segmentation is conducted with reference to high-resolution visual imagery acquired by UAVs for the purpose of monitoring tree phenology (Wu et al., 2021; Zhao et al., 2022, 2023). For monitoring the flowing phenology of individual trees in Borneo, Miura et al. (2023) performed ITC segmentation with reference to RGB images acquired from an observation crane. Jutras-Perreault et al. (2023) used a combination of ALS and visual imagery to segment ITCs for identifying snags. Dalponte et al. (2022) applied the region growing algorithm introduced by Dalponte and Coomes (2016) in order to automatically segment ITCs using lidar. The only article to attempt ITC segmentation exclusively using PlanetScope data is Reiner et al. (2023), who trained a convolutional neural network to segment ITCs across Africa; however, this model was only applied to segment trees in non-forest land cover types such as savannas and pastures, and also used the simplifying assumption that objects greater than 200 m<sup>2</sup> were multiple trees rather than a single crown.

Thus far, tree-based approaches using PlanetScope data have been adopted mostly for monitoring phenology (Miura et al., 2023; Wu et al., 2021; Zhao et al., 2022, 2023) or for assessing non-stand replacing disturbances (Dalponte and Coomes, 2016; Jutras-Perreault et al., 2023; Rodes et al., 2021), subtle phenomena where change can take place over extended periods of time and which may be highly variable at fine spatial scales. One of the potential advantages of a tree-based approach for applications such as these is that it may mitigate background noise from canopy gaps. Bendavid et al. (2023) observed that understory vegetation may bias assessments of forest condition which are based on common vegetation indices, with the effect being more pronounced in less dense stands. Such bias may be avoided by limiting the scope of the analysis to the crown; however, the capacity for PlanetScope to be used in this way depends on crown size, geometry, and alignment with PlanetScope pixels. The importance of crown characteristics for a tree-based approach is highlighted by Dalponte et al. (2022). By using a series of support vector machines and PlanetScope spectral features, they were able to predict tree species with an accuracy of 74.4 % and the presence of heartwood rot with an accuracy of 56.3 %; when only crowns greater than 9 m<sup>2</sup> (the area of a single PlanetScope pixel) were considered, accuracies increased to 78.3 % and 70.6 %. Zhao et al. (2022) addressed this consideration by excluding trees with crown diameter less than 3 m from their analysis.

**4.8.2.2. Sub-pixel monitoring.** Because PlanetScope data has high spatial resolution, it may be used to extract the spectral signatures of high-quality endmembers (i.e., pure pixels which represent distinct materials or landcover types). Several articles have leveraged this capability by using spectral mixture analysis for a variety of applications, mostly across tropical sites in South America. J. Wang et al. (2023) tested an unsupervised process to automatically identify endmembers for leafy canopy, leafless canopy, and shade across 16 tropical sites on 4 continents. First, they identified a list of candidate pixels within the fifth or ninety-fifth percentile reflectance values for several spectral features. A feedforward neural network was then iteratively applied in order to par this list down to an optimal set of endmember pixels. With these

“true” endmembers, they then used spectral unmixing to assess the deciduousness of each site by calculating the ratio of leafy to leafless pixels. This same procedure was later adopted by Song et al. (2024) to test how the spatial resolution of remote sensing data affects deciduousness predictions. Ping et al. (2023) applied spectral unmixing to a similar set of land cover types (photosynthetically active vegetation, non-photosynthetically active vegetation, and shadow) in order to track stand recovery from wind damage in the Amazon, although endmember pixels were manually selected using a red-NIR scatterplot. Petri et al. (2022) used the SMACC algorithm (Gruninger et al., 2004) to automatically select endmember pixels for green vegetation, soil, and shade, then applied spectral mixture analysis to investigate how sun angle affects surface reflectance at sites in the Amazon.

4.9. PlanetScope with other remote sensing data

Remote sensing data besides PlanetScope are featured in three quarters of articles in this review. Satellites with multispectral sensors are by far the most popular, with data from Sentinel-2 alone being used in 64 articles (Fig. 9). The next tier is active remote sensing data, such as

airborne laser scanning (ALS) and spaceborne synthetic aperture radar (SAR). Unmanned aerial vehicles (UAVs) and terrestrial platforms tend to be used the least in articles that feature PlanetScope.

4.9.1. Integration of PlanetScope data with other remote sensing data

In many of the reviewed articles, PlanetScope data is used with other remote sensing data in a complementary fashion to conduct an analysis or produce a product.

4.9.1.1. Validation. A common use for PlanetScope data is to create training and validation datasets for models developed using coarser resolution remote sensing data. For example, Mulverhill et al. (2023) used a time series of PlanetScope data to validate a change detection procedure based on 30 m Harmonized Landsat Sentinel-2 data. Takasaki et al. (2022) used PlanetScope data to verify the labels on a land cover map of the Peruvian Amazon which was generated using Landsat data. Reiche et al. (2021) and Welsink et al. (2023) each used PlanetScope to validate a forest disturbance alert system based on Sentinel-1. In most cases, validation is undertaken by visually inspecting the PlanetScope data. Likewise, other remote sensing data with spatial resolution higher

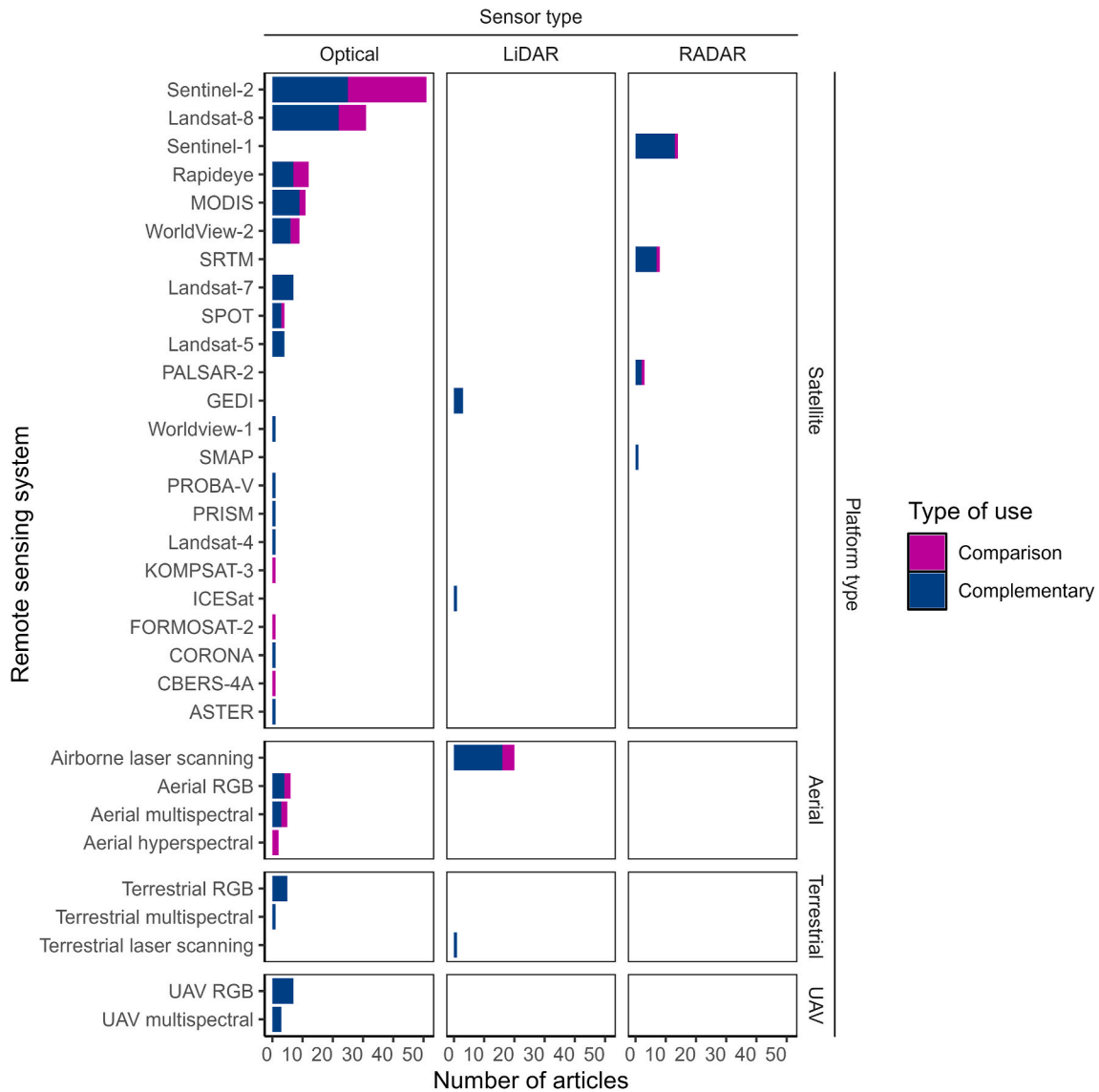


Fig. 9. The total number of articles that use data from each remote sensing system, as well as whether the data was integrated with PlanetScope in a complementary fashion or whether it was compared with PlanetScope for a particular monitoring application. Remote sensing systems are grouped by sensor and platform type. UAV: unmanned aerial vehicle.

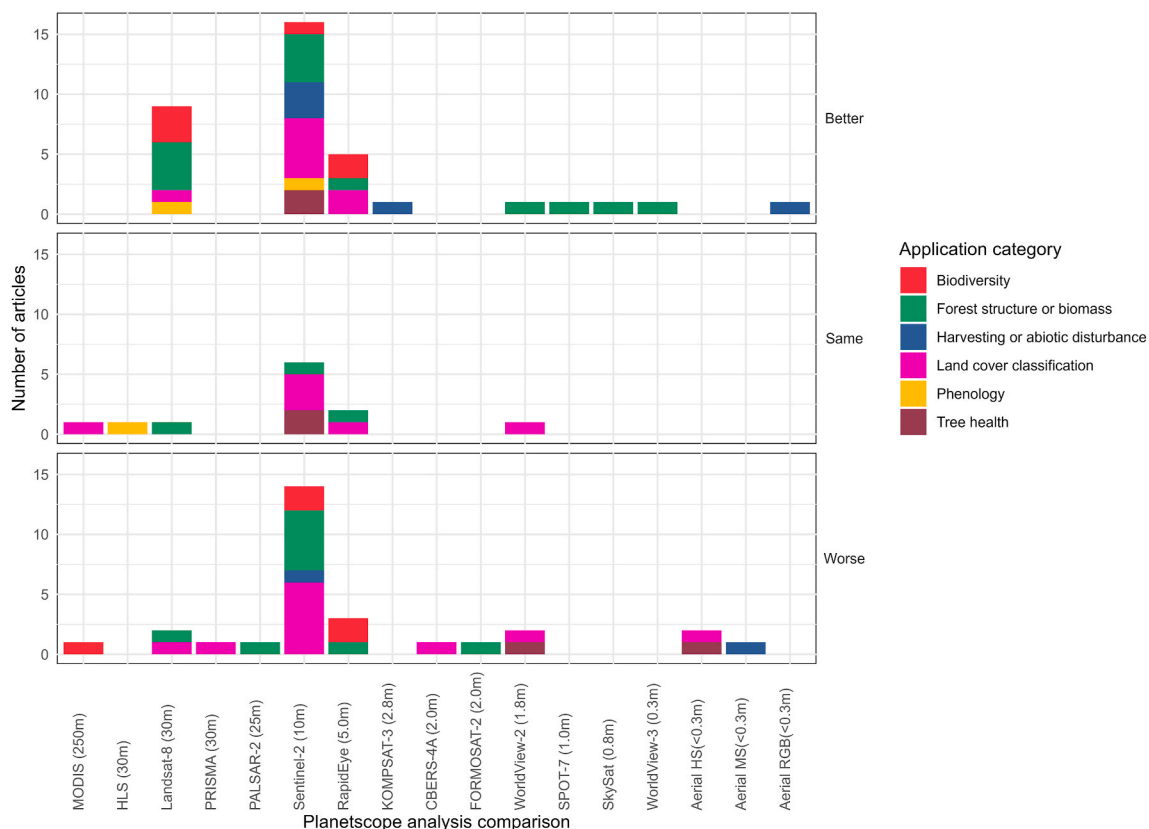
than 3 m have also been used to provide visual validation for analyses conducted using PlanetScope. The application where this is most common is in phenology monitoring, where ground-based optical sensors such as Phenocams are frequently used (e.g., Moon et al., 2021; Song et al., 2024).

**4.9.1.2. Image sharpening.** Several articles have explored the potential for using Sentinel-2 data which has been pan-sharpened with PlanetScope for mapping urban greenspace (Gašparović et al., 2018b) and classifying different forest types (Ye et al., 2021, 2022). Each of these articles uses the variational method described in Gašparović and Jogun (2018). In each case, models developed using pansharpened data have higher accuracy than those developed using PlanetScope or Sentinel-2 data alone. The only instance of PlanetScope data being pan-sharpened is presented by Siti-Nor-Maizah et al. (2022), who used Worldview-1 with a spatial resolution of 0.5m and the Gram-Schmidt method in order to detect harvested areas in Malaysia. More recently, Kong et al. (2023) have experimented with using a generative adversarial network to increase the spatial resolution of historical Landsat imagery using PlanetScope.

**4.9.1.3. Time series expansion.** Other high-spatial resolution remote sensing data may be used with PlanetScope for change detection applications which span time periods before PlanetScope became available. For example, Negi et al. (2022) analyzed land cover change in northern India over almost 5 decades using CORONA satellite images from 1972 and PlanetScope scenes from 2020. In another long time series, Veettil et al. (2024) used a combination of PlanetScope, RapidEye, Sentinel-2, and several generations of Landsat to monitor changes

in mangrove forests between 1988 and 2022. Lucanus et al. (2021) used RapidEye imagery from 2014 and PlanetScope data from 2020 to evaluate flooding in the Brazilian Amazon. To study the link between deforestation and charcoal production in Mozambique, Sedano et al. (2021) used a combination of Worldview-2 and RapidEye for the years 2013–2016 then switched to PlanetScope for the years 2017–2019.

**4.9.1.4. Feature set expansion.** In many instances, superior model performance is achieved by incorporating variables from other remote sensing datasets in addition to PlanetScope. Additional spectral data from other passive optical sensors may be used to complement the spectral bands of PlanetScope. For example, the red edge and shortwave infrared bands of Sentinel-2 have been used in addition to PlanetScope data for predicting plant area volume density (Mulatu et al., 2019) and aboveground biomass (Matiza et al., 2024b). Besides spectral information, Silveira et al. (2023) also demonstrated that including remote sensing datasets with different spatial information may improve model performance, finding that bird species richness in forested sites across the United States was predicted best when data from RapidEye, Landsat-8, and MODIS were included in addition to PlanetScope. Model performance has also been improved by incorporating active remote sensing data. Rösch et al. (2022) found that slope, aspect, and elevation layers derived from ALS were significant for mapping mountain pine stands in northern Italy, while Matiza et al. (2024b) found that the slope and elevation products were significant for predicting aboveground biomass in South Africa. For predicting the species of street trees in Brussels, Neyns et al. (2023) found that the optimal feature space included both high-resolution aerial multispectral imagery and a canopy height model derived from ALS in addition to PlanetScope bands. Even



**Fig. 10.** Results of articles which compare PlanetScope with other types of remote sensing data for particular forest monitoring applications. The 73 comparisons come from 41 articles. Comparisons are “better” if using PlanetScope data produced a better result (e.g. more accurate models, sooner detection of change), “worse” if using the other remote sensing data produced a better result, and “same” if PlanetScope and the other data had similar performance (i.e. <1 % difference in model accuracy). The remote sensing technologies which have been compared with PlanetScope are arranged along the x-axis in ascending order of spatial resolution (indicated in brackets). “HS” is “hyperspectral”, “MS” is “multispectral”, and “HLS” is “Harmonized Landsat Sentinel-2”.

without being processed into a topographic or canopy height product, the C-band of Sentinel-1 was selected as a significant feature by both [Mulatu et al. \(2019\)](#) and [Matiza et al. \(2024b\)](#).

#### 4.9.2. Comparison with other remote sensing data

Forty-one articles compared PlanetScope with other remote sensing datasets by applying the same modelling or analysis approach to each dataset for the same forest monitoring application in the same area of interest. These articles contain 73 comparisons since many individual articles present multiple comparisons ([Fig. 10](#)). The remote sensing sources with the most comparisons are Sentinel-2 (34 comparisons), Landsat-8 (12), and RapidEye (8).

In 40 % of comparisons, using other remote sensing data resulted in superior model fit, accuracy, or correlation strength than that of PlanetScope. In 46 % of comparisons, PlanetScope data had superior performance, and in 14 % of comparisons the compared datasets were relatively similar to PlanetScope (e.g., there is less than 1 % difference between them). In most cases, the difference resulting from using PlanetScope versus other datasets was relatively small (e.g., less than  $\pm 0.1 R^2$  or 10 % accuracy). However, there are several cases where using PlanetScope produced substantially better ([Gyamfi-Ampadu et al., 2021](#); [Song et al., 2024](#)) or substantially poorer ([Baloloy et al., 2018](#); [Jutras-Perreault et al., 2023](#)) results than using other remote sensing data.

In many articles where other remote sensing datasets produced superior results, models based on the other data leveraged features which are not available when using 4-band PlanetScope data. In particular, short-wave infrared and red edge bands—or spectral indices derived from these—are often listed as important model features in comparisons where the other dataset was better (e.g., [Dalponte et al., 2020](#); [Mulatu et al., 2019](#); [Ye et al., 2021](#); [Ziegelmaier Neto et al., 2024](#)). For assessing aboveground biomass using spaceborne SAR, [Madundo et al. \(2023\)](#) achieved superior results using PALSAR-2 L-band backscatter data but worse results using Sentinel-1 C-band.

There was no clear relationship between the spatial resolution of the dataset being compared and whether PlanetScope resulted in better model performance. While datasets with finer spatial resolution than PlanetScope have consistently been used to produce models with better performance, these models have also more often than not incorporated different spectral features, raising the question of whether the results arise from differences in spatial or spectral resolution. When PlanetScope is compared with coarser spatial resolution datasets, results are mixed. For example, [Silveira et al. \(2023\)](#) found that PlanetScope data was better than RapidEye, Sentinel-2, and Landsat-8 but poorer than MODIS or a combined multiscale dataset for developing multivariate linear models to predict bird species richness across the United States.

In cases where the temporal resolution of the data is important for the analysis, PlanetScope is often rated as being more useful than other remote sensing data. [Ping et al. \(2023\)](#) compared the effectiveness of PlanetScope monthly basemaps with Landsat-8 scenes for monitoring forest recovery following wind damage in the Amazon; they found that PlanetScope was better for showing trends by providing new images at shorter and more regular intervals. [Michael et al. \(2018\)](#) found that PlanetScope could be used to more accurately assess wildfire severity than Sentinel-2; they attribute this to the fact that the first PlanetScope scene was acquired much sooner after the fire than the first Sentinel-2 scene, and therefore was not influenced by the regrowth of seral vegetation.

At least two articles suggest that the quality of PlanetScope data may affect its usefulness relative to other remote sensing data. For predicting aboveground biomass in a mangrove forest, [Baloloy et al. \(2018\)](#) achieved an  $R^2$  of 0.4 using PlanetScope and  $R^2$  values greater than 0.9 using Sentinel-2 and RapidEye. While differences in spatial or spectral resolution may have contributed to this disparity, another potential factor is that they were using PlanetScope data acquired in 2015, some of the oldest data used by an article in this review. Because the quality of

PlanetScope data has improved over time as incremental improvements in technology or preprocessing methods have been introduced, the early acquisition date of the data used in this article may have contributed to the relatively low performance obtained using PlanetScope. In addition, [Silveira et al. \(2023\)](#) compared models for predicting bird species richness using RapidEye, Sentinel-2, Landsat-8, MODIS, and a combined multiscale dataset with models fit using PlanetScope data that had been resampled to match the spatial resolution of each type of remote sensing data. They found that the models trained on the resampled PlanetScope data had  $R^2$  values which were 0.06–0.16 lower than the corresponding models of trained on other remote sensing data. The largest difference occurred in the comparison with MODIS, the dataset with the most similar temporal resolution to PlanetScope. These findings suggest that noise in the PlanetScope data may have influenced the analysis.

## 5. Discussion and future directions

The major findings of this review are presented in [Table 5](#), along with recommendations for using PlanetScope data and opportunities for future research. Each is discussed in more detail below.

To date, a dominant theme in PlanetScope research has been monitoring land cover change or disturbances in tropical forests. The short revisit time of PlanetScope makes it well-suited to this task since many tropical regions of the world experience high levels of year-round cloud cover, making data acquisition difficult when using optical Earth observation satellites with less frequent revisit. Nonetheless, the inability of PlanetScope to acquire surface reflectance data under cloudy conditions presents a barrier to use in many regions ([Reiche et al., 2021](#)). To address this shortcoming, there is potential to harmonize PlanetScope with SAR satellites such as Sentinel-1 which are capable of observing the Earth's surface through cloud. While previous studies (e.g., [Tang et al., 2023](#)) have integrated SAR with optical data from other sensors for near-real time forest monitoring, the application of such integration with PlanetScope has not yet been explored. Doing so presents an avenue for improving near-real time monitoring.

PlanetScope has been used in a wide range of forest monitoring applications; however, the distribution of these applications across different forest ecosystems has been uneven ([Fig. 8](#)). For example, although many articles in this review are concerned with aboveground biomass, research has been highly concentrated in tropical forests as well as non-forest ecosystems, and there are no articles in this review using PlanetScope to estimate aboveground biomass in either temperate or boreal forests. Therefore, there remain many opportunities to apply PlanetScope data in novel contexts. In general, boreal forests have been underrepresented in PlanetScope research: although they constitute the world's second largest terrestrial biome ([Kayes and Mallik, 2020](#)), they are only featured in 6 % of articles in this review. Since it is predicted that climate change may alter the disturbance regimes of boreal forests to a greater degree than in other types of forest ([Seidl et al., 2017](#)), developing techniques which leverage PlanetScope data for change detection in boreal forests remains an important area of research. There are also relatively few articles which use PlanetScope for applications related to biodiversity monitoring other than tree or stand classification. The strongest models for predicting biodiversity often incorporate data from multiple spatial resolutions ([Silveira et al., 2023](#); [Torresani et al., 2024](#)); therefore, there is potential to leverage PlanetScope's fine resolution data for this purpose alongside coarser resolution data.

Although the near-daily global coverage of PlanetScope enables the analysis of dense time series over large areas, most investigations use PlanetScope to study relatively small areas which are encompassed by a single scene, or time series with intervals of one month or longer between images. While the monetary cost of accessing PlanetScope data may limit its usage in commercial settings, it is unlikely that cost is a factor for the articles in this review since PlanetScope data may be freely accessed for research or educational purposes via a non-commercial license ([Planet Labs, 2020, 2025](#)). It is more likely that the scope of

**Table 5**  
Summary of review findings and opportunities for future research using PlanetScope data.

Research question	Summary of findings	Opportunities for further research
What forest ecosystems, phenomena, and attributes has PlanetScope been used to study?	The bulk of research using PlanetScope data has been devoted to tropical forests. The main uses of PlanetScope have been mapping the locations of forests or trees, modelling aboveground biomass, and mapping different stand replacing disturbances.	Expand research in boreal forests. Further explore the potential of PlanetScope for applications related to biodiversity monitoring.
What are the spatiotemporal characteristics of the PlanetScope datasets used in these studies?	Most articles which use time series data use PlanetScope for monthly monitoring. Most studies use PlanetScope to monitor areas which are smaller than a single PlanetScope scene. Superior model performance often results from resampling PlanetScope data to other spatial resolutions.	Resample PlanetScope data to determine the optimal spatial resolution for a given task. Leverage radiometric correction to enable analyses that incorporate multiple PlanetScope scenes.
How has PlanetScope data been used in conjunction with other remote sensing data and how do models trained using PlanetScope data perform relative to other remote sensing datasets?	The fine spatial resolution of PlanetScope has been leveraged to enhance analyses on coarser resolution data by allowing pan sharpening or validation. ALS or multispectral datasets may be used with PlanetScope to enable fine-scale analysis such as individual tree monitoring. Models trained on PlanetScope often underperform those trained on other remote sensing data when the other data has higher spectral resolution or when spatial resolution of the other data is a better fit for the application.	Explore the potential of using fused datasets that incorporate remote sensing data with a range of spatial and spectral resolutions.
What approaches have been developed for addressing PlanetScope's data quality challenges?	A minority of articles use additional pre-processing to improve the quality of PlanetScope data. Those which do primarily use additional pre-processing to improve radiometric consistency.	Produce and popularize open-source tools for improving radiometric consistency, geometric consistency, and masking anomalous pixels. Compare the relative effectiveness of different radiometric correction methods.
What are the most common approaches or algorithms used for processing PlanetScope data and how has the data been used in conjunction with other remote sensing data or ancillary datasets?	Analysis approaches are largely consistent with those applied to other medium or high-resolution optical satellite data. Machine learning methods—especially random forest and deep learning—dominate for both classification and regression tasks. Object-based image analysis results in moderate improvements over pixel-based methods for classification. In addition to the RGB-NIR bands and NDVI, texture features which capture the spatial relationship between pixels are prominently used in investigations involving PlanetScope.	Further explore object-based classification methods. Explore the potential for using additional Super Dove bands and the spectral indices that they make available.
How have the high spatial and temporal resolutions of PlanetScope data been leveraged for near-real time monitoring or precision forestry?	Most work on near-real time monitoring has been based on the analysis of bitemporal data from before and after discrete change events. Promising applications of PlanetScope which leverage its high spatial resolution include individual tree monitoring and spectral mixture analysis.	Improve near-real time monitoring through integration with other datasets such as synthetic aperture radar. Explore potential for segmenting tree crowns using only PlanetScope data.

investigations using PlanetScope is limited by the high computational demands associated with processing fine resolution data. Another potential factor is the possibility that incorporating many PlanetScope scenes could increase the noise resulting from imperfect cross-calibration between PlanetScope sensors or from using data acquired under different illumination or atmospheric conditions. Radiometric correction is the aspect of data quality which has received the most attention in the literature, and while various methods have been introduced for improving the radiometric quality and consistency of PlanetScope data, investigation is still ongoing since there have been few comparisons evaluating the relative effectiveness of these methods. In addition, several highly-cited methods (e.g., [Houborg and McCabe, 2018](#)) have not been tested by articles in this review for forest monitoring applications. One possible reason why little work has been done to compare different methods—and why radiometric correction other than the preprocessing offered by Planet Labs has not been more widely used in this review—is the fact that few methods are available for easy implementation in publicly available software repositories. One of a small number of examples is the method proposed by [Wegmueller et al. \(2021\)](#).<sup>4</sup> Since radiometric correction techniques may involve complex workflows which incorporate other types of remote sensing data besides PlanetScope, implementing them from scratch represents a technical obstacle for many practitioners. Therefore, an investigation into radiometric correction that both compares different methods and produces the software allowing their implementation would represent a valuable

contribution to PlanetScope research. Aside from radiometric correction, errors with masking noisy pixels—such as those containing cloud—is the second greatest challenge reported by PlanetScope users in the reviewed articles. While simple manual editing of noisy pixels is possible on a few images, they present a significant obstacle when working with numerous images, in which case automatic masking is the only practical solution. Fortunately, several approaches for automatic masking have been developed to address this issue. In particular, the results reported with the STI-ACSS algorithm ([Wang et al., 2021](#)) for masking cloud and cloud shadow are promising, with software for its implementation publicly available.<sup>5</sup> As of writing, this method has not been compared with Planet's latest UDM2.1 data quality asset, yet it offers a reasonable and tunable pre-processing alternative when using extensive image timeseries. Likewise, the AROSICS algorithm ([Scheffler et al., 2017](#)) shows promise for automatically co-registering PlanetScope images and is also available as a Python library,<sup>6</sup> facilitating its easy implementation into pre-processing workflows.

When the temporal dimension of data is crucial, PlanetScope offers distinct advantages over other remote sensing data: it facilitates more precise analysis of change events by enabling data acquisition nearer in time to those events, and enhances trend analysis through the collection of denser time series. When the temporal dimension is less important, other data often provide superior results over PlanetScope either

<sup>4</sup> [https://github.com/swegmueller/LORACCS\\_Mosaic\\_Correction](https://github.com/swegmueller/LORACCS_Mosaic_Correction).

<sup>5</sup> <https://github.com/Global-ecology-and-remote-sensing/PlanetScope-cloud-detection>.

<sup>6</sup> <https://github.com/GFZ/arosics>.

because i) they have higher spectral resolution, ii) they provide useful non-spectral features (e.g., SAR), or iii) their spatial resolution is a better match for the given application. This third point is underscored by the finding that, in many cases, higher model performance may be obtained by resampling PlanetScope data to other spatial resolutions. Therefore, one potential way of using PlanetScope data could be to resample it in the preliminary stages of an investigation in order to identify the optimal spatial resolution for the analysis, a procedure which is analogous to the one advocated for by Woodcock and Strahler (1987). This step may help practitioners decide what type of data to proceed with on the basis of spatial resolution: if resampling PlanetScope to coarser resolutions proves advantageous and its short revisit time is not being leveraged, then a user might consider alternatives such as Sentinel-2 or Landsat-8, which have the advantages of being freely available, detecting a wider range of optical wavelengths, and being less noisy due to having fewer sensors and onboard calibration (Frazier and Hemingway, 2021). The high spatial resolution of PlanetScope also lends itself better to certain analytic approaches such as object-based image analysis. Object-based analysis is appropriate in cases where the spatial resolution of the data is smaller than the object under consideration (Blaschke, 2010); therefore, data such as PlanetScope with high spatial resolution allow it to be more widely used. Object-based approaches have the potential to reduce noise and computational demands as well as allowing the extraction of features based on object dimensions or geometry (Blaschke, 2010; Nasiri et al., 2023; Sedano et al., 2021); while few articles in this review explicitly compare pixel and object based methods, those which do suggest that the latter may result in modest improvements in classification accuracy. Given this finding, we suggest that object-based approaches are underutilized for monitoring forests with PlanetScope: while one systematic review (Phiri et al., 2020) suggests that object-based image analysis is the dominant approach for land cover classification using Sentinel-2 data, only 20 % of articles in this review of PlanetScope use object-based methods. Future research should continue to explore the potential for using object-based image analysis with PlanetScope data for forestry applications.

Monitoring ITCs is a special case of object-based analysis where PlanetScope shows great promise. In most articles where PlanetScope is used for ITC monitoring, ITC segmentation is accomplished using aerial RGB or ALS data with higher spatial resolution than PlanetScope. While the use of these datasets assures segmentation accuracy, reliance on them potentially limits a user's ability to leverage PlanetScope's wall-to-wall coverage and high temporal resolution since aerial data are usually gathered infrequently and over relatively small spatial areas. A potential solution could be to use very high-resolution satellite data such as Worldview for segmentation. However, a more parsimonious solution would be to use PlanetScope data itself for ITC segmentation. The work of Reiner et al. (2023) suggests that applying deep learning to PlanetScope for identifying ITCs may be effective in situations where the canopy is not closed and when there is minimal interference from understory vegetation.

## 6. Suggestions for using PlanetScope data

As a commercial satellite constellation, usage of PlanetScope has been moderate when compared with freely available satellite data such as Landsat and Sentinel. Although the first PlanetScope satellites were launched a year before Sentinel-2, a Google Scholar search for "Sentinel-2" in 2025 yields an order of magnitude more results than a search for "PlanetScope" does, signalling that the former is far more widely used. This gap has developed in spite of the fact that Planet Labs offers generous licenses allowing use of PlanetScope data by research institutions (Planet Labs, 2025), in addition to having a longstanding contract with the Government of Norway to make available basemap data for non-profit organizations to monitor tropical forests (Planet Labs, 2020). While an early reputation for lower data quality (Frazier and Hemingway, 2021) may have contributed to this lag, another likely

factor is the cost of PlanetScope limiting its uptake by the private sector. To justify the use of PlanetScope, it is in the interest of a potential user to understand under what circumstances it may offer significant advantages over free data such as Sentinel-2, as well as how to prepare and use the data once it has been acquired. Based on the results of this review, we have developed the following list of suggestions for when and how to use PlanetScope data in forest monitoring. Note that suggestions may not apply for every use-case.

- The use of PlanetScope data should be considered when its high temporal resolution is significant for the analysis or when its high spatial resolution can be leveraged via an object-based approach.
- The user might consider resampling PlanetScope data to other spatial resolutions in order to discern the optimal spatial resolution for their application, or to use lower spatial resolution data while leveraging PlanetScope's short revisit time. If the high temporal resolution is not important and lower spatial resolutions yield better results, the user may consider proceeding with other types of optical remote sensing data.
- When multiple PlanetScope scenes are used, their radiometric and geometric consistency should be assessed and tested. If the consistency is found to be low, then additional correction procedures should be considered.
- Although issues with data quality may persist, the consistency of data quality can be improved by using data acquired by a single satellite, a single generation of satellite, or under similar illumination conditions. For monitoring at longer time intervals, composite images may also be employed to compensate for differences between sensors or acquisition conditions.
- To take advantage of incremental technological improvements introduced by Planet Labs, data from the newest possible generation of sensor should be used.
- If issues with radiometric consistency can be managed, then scene products should be favored over basemaps in order to maximize temporal and spatial resolution.
- Features based on the red, NIR, and red edge bands should be tested for model development because of their sensitivity to a variety of vegetation properties.
- When their use is appropriate, non-parametric machine learning methods often produce superior accuracy or model fit.

## 7. Conclusion

We conducted a systematic literature review on the use of PlanetScope optical CubeSat data for monitoring forests and trees. PlanetScope's unique combination of high spatial resolution, high temporal resolution, and global coverage has made it a valuable tool for applications such as mapping different types of land cover, analyzing phenological trends, and monitoring stand-replacing disturbances, particularly in tropical forests. These capabilities have been widely leveraged in the remote sensing community, showcasing the versatility of PlanetScope data. While many studies demonstrate the effectiveness of PlanetScope, some challenges remain, particularly with the temporal and spatial scale of certain investigations. Variability in radiometric quality between PlanetScope sensors is one such concern; although several techniques have been proposed to address this issue, there is still a need for further research to better understand and mitigate its impact. Despite these challenges, there is marked potential for using PlanetScope data for near-real time monitoring and precision forest management. By improving the understanding of radiometric correction methods and integrating PlanetScope data with other remote sensing sources, future research can unlock even greater potential for forest monitoring applications.

In summary, PlanetScope offers promising opportunities for advancing forest monitoring at multiple scales. With continued refinement of techniques and tools, its role in the remote sensing landscape is

poised to expand.

### CRedit authorship contribution statement

**Spencer G. Shields:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicholas C. Coops:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Alexis Achim:** Writing – review & editing, Funding acquisition. **Richard C. Hamelin:** Writing – review & editing. **Christopher Mulverhill:** Writing – review & editing.

### Declaration of generative AI

During the preparation of this work, the authors made sparing use of ChatGPT to improve the readability of the paper by helping with spelling, grammar, word choice, and syntax. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Data availability

The data and code used for this review are available at <https://github.com/Spencer-Shields/planetscope-forests-lit-review-git-repo>

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