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# A systematic review of remote sensing data to assess dry forests attributes.

## Una revisión sistemática de los datos de sensores remotos para evaluar atributos de los bosques secos.

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SUMMARY

Ecological indicators are widely used to assess vegetation attributes and can be quantified through field-based and/or remote sensing data. Particularly, advances in remote sensing have allowed monitoring of dry forest attributes across multiple spatiotemporal scales. The objectives were to analyze the recent state-of-the-art in using remote sensing data as ecological indicators to assess dry forest attributes; identify the data source of remote sensing indicators used; and identify the geographical distribution of these studies. A systematic search was conducted for original research articles that used remote sensing data as ecological indicators of dry forests attributes. Composition indicators were assessed with the same frequency at species/population and landscape/region hierarchy levels. However, structural indicators were mainly assessed at the species/population level, and function indicators at the community/ecosystem level. Over 60 % of the articles considered one ecological indicator, 20.45 % two, and 18.18 % used three indicators. Over 47 % considered field surveys and remote sensing data to assess dry forest attributes, and more than 52 % only had remote sensing data. Four out of the 88 articles analyzed report a weak relationship between field surveys and remote sensing data. Landsat and MODIS products were the most frequently used, with South America being the most studied continent. Observations and products from a single sensor, as well as using only one ecological indicator or one hierarchy level, would not be enough to represent the complexity of dry forest ecosystems.

*Keywords:* ecological indicators, remote sensors, dryland ecosystems, composition, structure and function.

RESUMEN

Los indicadores ecológicos son ampliamente usados para evaluar los atributos de la vegetación y pueden cuantificarse mediante datos de campo y/o de teledetección. Particularmente, los avances en la teledetección han permitido monitorear las condiciones del bosque seco a través de múltiples escalas espacio-temporales. Los objetivos fueron analizar los últimos avances en el uso de datos obtenidos de sensores remotos como indicadores ecológicos para evaluar los atributos de los bosques secos; identificar la fuente de datos de los indicadores de teledetección utilizados; e identificar la distribución geográfica de estos estudios. Se realizó una búsqueda sistemática de artículos de investigación originales que utilizaron datos de sensores remotos como indicadores ecológicos de los atributos de los bosques secos. La mayoría de los 78 artículos seleccionados utilizaron indicadores de composición a nivel de paisaje/región, indicadores de estructura a nivel de población/especie e indicadores de función con frecuencia similar en ambos niveles. Más del 40 % consideró dos de los tres indicadores ecológicos. Más del 50 % solo usó datos de sensores remotos como indicadores de composición y más del 90 % como indicadores de función; sin embargo, casi el 70 % consideró solo datos de estudios de campo como indicadores de estructura. Los productos Landsat y MODIS fueron los más utilizados, siendo Sudamérica el continente más estudiado. Las observaciones y productos de un solo sensor, así como el uso de un solo indicador ecológico o un nivel jerárquico, pueden no ser suficientes para representar la complejidad de los ecosistemas de bosques secos.

*Palabras clave:* indicadores ecológicos, sensores remotos; ecosistemas de tierras secas, composición, estructura y función.

## INTRODUCTION

Currently, drylands stretch across more than 40 % of the Earth's land surface, but recent climate model simulations predict that they could extend for over 50 % due to regional warming and the expansion of urban centers (Bastin *et al.* 2017). In drylands, woody species play a fundamental role in climate change by acting as sinks and sources of carbon, providing habitats for many animals and plants species, and supplying other vital ecosystem services such as regulation of hydrobiological cycle, protection from erosion, and supply of food and raw materials (Thompson 2011, Hansen *et al.* 2013). Moreover, woody species establish fertility islands that increase the system's total biodiversity (Villagra 2000, Rossi and Villagra 2003, Cesca *et al.* 2012, Campos *et al.* 2017). Despite the crucial role of woody species in dry forests, there are important gaps in basic knowledge of their patterns and processes.

Spatiotemporal changes in dryland vegetation patterns represent a consistent indicator of a catastrophic shift from a vegetated to a degraded non-vegetated state (Veldhuis *et al.* 2022). However, knowledge of dry forests is relatively limited because of their being structurally and functionally very dynamic, so carrying out continuous field measurements of these ecosystems is a great challenge (Smith *et al.* 2019). Moreover, it is important to consider that patterns and processes operate on a wide range of spatial and temporal scales, and there may be no single correct scale (Levin 1992). For this, it is crucial to understand how information is transferred from fine to broad-scale, *i.e.* from the leaf to the ecosystem to the landscape and beyond (Levin 1992). Therefore, an exhaustive analysis of vegetation conditions should consider aspects of structural components and ecological processes into account, at several hierarchy levels and consider different scales in time and space (Noss 1990). However, such a comprehensive assessment would be impossible and impractical because it is time-consuming, and often too expensive (Lawley *et al.* 2015). In consequence, ecologists proposed the use of a subgroup of indicators to know current dry forest conditions (Noss 1990, Dale and Beyeler 2001). The correct choice of indicators to assess ecological attributes of an ecosystem should consider specific objectives, the scale of interest, logistic and funding resources, and management implications (Dale and Beyeler 2001). Moreover, the selected indicators should be ecologically relevant, reliable, and repeatable to allow comparison and monitoring, be sensitive to stressor factors, be able to change with management practices, and allow for continuous and standardized assessment (Noss 1990).

Considering the multiple facets of an ecosystem, there are diverse ecological indicators according to its three attributes: composition (identity and variety of elements), structure (three-dimensional arrangement or physical organization), and functional attributes (ecological processes and history) (Noss 1990). Combined, these attributes define the wholeness and complexity of an ecological system, therefore, their presence, absence, or variations reflect changes at one or various hierarchy levels, and possibly at different spatiotemporal scales (Dale and Beyeler 2001). The indicators of these attributes can be obtained from field-based measurements and/or from remote sensing data. The first method has focused mainly on taxonomy, sometimes on other compositional and structural attributes, and rarely relates to the extent of the system's functionality (Lawley *et al.* 2015). Even though this method provides indispensable information, it could be ineffective to obtain vegetation covers across broad spatial extents due to its high cost and time-consuming requirements (Xie *et al.* 2008). Remote sensing data afford systematic, spatial, and temporal data on land surface (Nagendra 2001, Lawley *et al.* 2015), and is therefore considered the most promising approach to studying an ecological system in its wholeness (Hall *et al.* 2006, Smith *et al.* 2019). Moreover, it is being increasingly recognized for its applicability in assessing vegetation conditions (Campos *et al.* 2018, Campos *et al.* 2022), and in mapping land use/land cover change; moreover, as a proxy of biodiversity at different spatial scales (Bradley *et al.* 2012, Irisarri *et al.* 2012). A right selection of the remote sensing data resolution (*i.e.* spatial, spectral, temporal) is defined by the vegetation attributes that researchers want to accurately measure (*i.e.* temperature of leaves, phenology, canopy structure and cover, patch distribution, and configuration) (Lawley *et al.* 2015). Therefore, researchers should have a prior knowledge of the vegetation characteristics to be measured in order to select the appropriate imagery and study methods.

Notwithstanding, both detection and monitoring of dry forest dynamics with remote sensing data are shaped by particular challenges, such as a great effect of soil, senescent or inactive vegetation, sparse and high spatial heterogeneity of vegetation canopies, unpredictable rainfall, and frequent periods of drought (Bastin *et al.* 2017). Remote sensing data developed and applied in other forests do not usually have a good enough fit and accuracy to assess and estimate dry forest attributes (Smith *et al.* 2019). Particularly, challenges are related to the estimation of tree abundance, structure and distribution, biomass, productivity, and phenology. Therefore, the ecological indicators used for their evaluation should be specifically tailored to their characteristics, since the dynamics and processes of dry forests differ from other types of forests. In this context, we conducted a systematic search for articles to determine trends in the use of remote sensing data as ecological indicators of dry forests and identify key knowledge gaps that need to be addressed. The objectives of this systematic review are: 1) to evaluate the recent state-of-the-art in using remote sensing data as ecological indicators to assess dry forest attributes; 2) to identify the data source of remote sensing indicators used; and 3) to identify the geographical distribution of studies that use remote sensing data as ecological indicators to assess dry forest attributes.

## METHODS

For this systematic review, we used the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Liberati *et al.* 2009). A systematic search was conducted for original research articles dealing with the use of remote sensing data as ecological indicators of vegetation attributes in dry forests. Figure 1 summarizes the methodology and the steps followed for article selection.

The systematic review included research articles from the years 2000 to 2022, on four online bibliographic databases: 1- Google Scholar, 2- ResearchGate, 3- ScienceDirect, and 4-Taylor & Francis. The following search terms and Boolean operators were used in the search for research articles: (i) ecological indicator AND dry forest OR dry woodland; (ii) remote sensing AND dry forest OR dry woodland.

At the screening step, we applied the first filter to remove studies of ecological indicators in other ecosystems, studies covering other dry forest topics, duplicates, reviews, theses, book chapters, and conference abstracts (figure 1). At the eligibility step, we applied a second filter through a systematic manual checking of titles and abstracts. In order to select only original research articles relevant to the topic, we considered the following eligibility

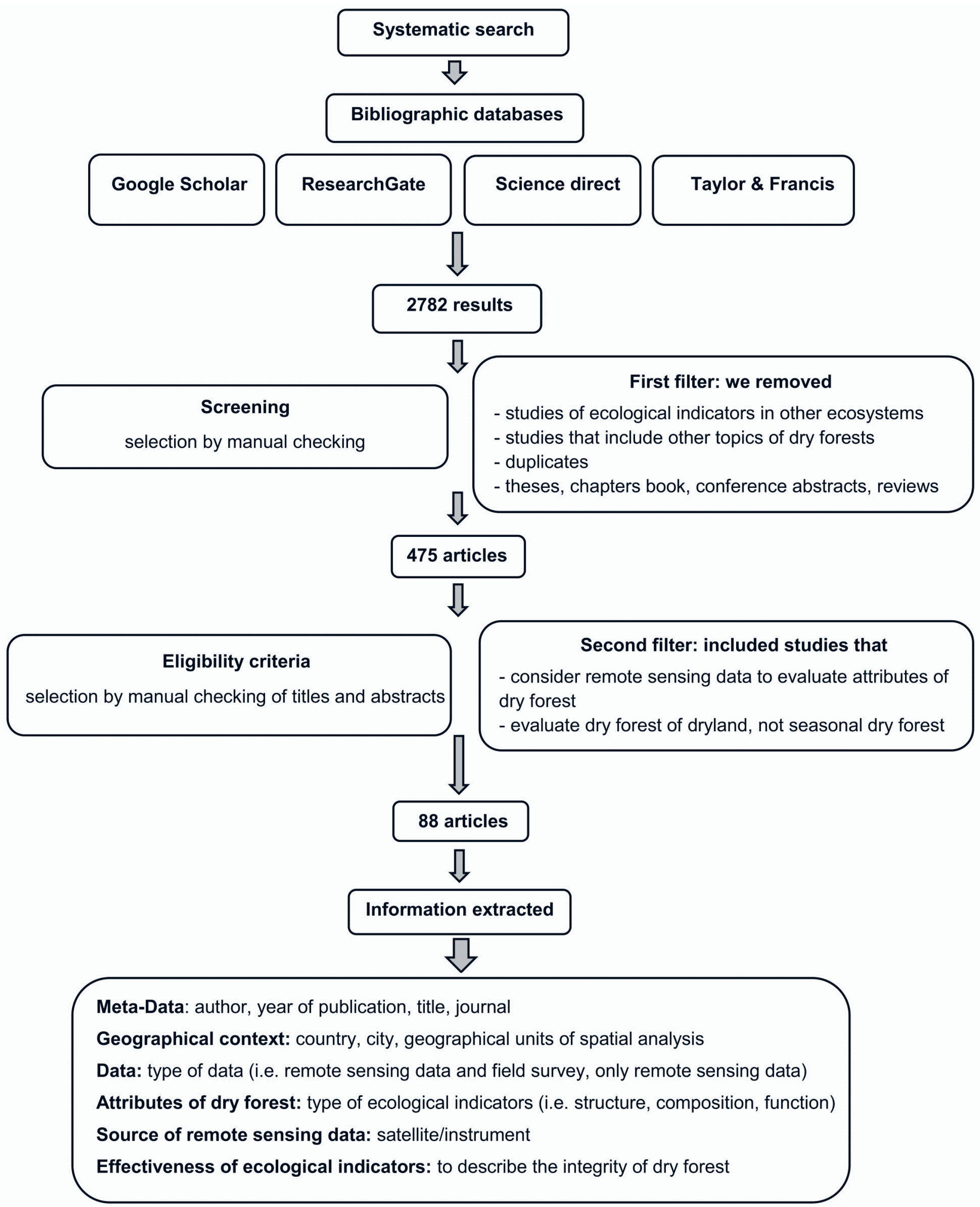


**Figure 1.** Scheme of steps followed in the systematic search for articles.

Esquema de los pasos que se siguieron en la búsqueda sistemática de artículos.

criteria: (1) articles that consider remote sensing data as ecological indicators to evaluate dry forest attributes, (2) those that evaluate dry forests of dryland biomes (annual precipitations lower than 1,000 mm), not seasonally dry tropical or subtropical forests (figure 1).

For each selected publication, we manually extracted information, *i.e.* publication meta-data, geographical context, and specific context of research: type of data, type of ecological indicators (*i.e.* composition, structure, function), data source, effectiveness of ecological indicators (to assess ecosystem condition and integrity), monitoring of ecosystem changes (focusing on structure and functionality of trees) (table 1). We classified the ecological indicators used in each research article according to the three ecosystem attributes (*i.e.* composition, structure, function) originally proposed by Noss (1990) and adapted by Dale and Beyeler (2001), considering three study levels (*i.e.* species/population, community/ecosystem, landscape/region; table 2 and 3). As composition indicators, we included variables related to presence of tree species, abundance and diversity. As structure indicators, we considered variables related to morphological features of tree species and physical features of forest ecosystems. As function indicators, we included variables that directly or indirectly measure ecosystem processes and functions.

## RESULTS

The systematic review returned 2,782 records from the four online bibliographic databases, and as a result of the evaluation process, 88 articles met our selection criteria and were included for analysis. The information extracted from each article is in SupplMat1 (*i.e.* meta-data, geographical context, and specific context of research), SupplMat2 (data, dry forest attributes), and SupplMat3 (source of remote sensing data, effectiveness of ecological indicators, monitoring of ecosystem changes).

The ecological indicators assessed in these research articles are described in table 2, 3 and 4, and were classified at all three hierarchy levels: (1) species/population, (2)

**Table 2.** The composition indicators considered in research articles were classified at the three hierarchy levels. Below each level is the percentage of articles that considered that level for each indicator.

Los indicadores de composición considerados en los artículos de investigación se clasificaron siguiendo los tres niveles de jerarquía. Debajo de cada nivel se encuentra el porcentaje de artículos que consideraron ese nivel para cada indicador.

| Level hierarchy | Composition |
|---|---|
| Species / population 42.50 % | Species identity |
| | Species occurrence |
| | Species density |
| | Above Ground Biomass (AGB) |
| | Tree volume / wood density |
| | Relative abundance |
| | Status / health |
| | Cover of vegetation |
| Community / ecosystem 15.00 % | Diversity (richness, evenness) |
| Landscape / region 42.50 % | Patch types (land cover classes) |

**Table 1.** A. Organization of the data extracted from each article about meta-data and geographical context. B. Organization of the data extracted from each article about type of data, dry forest attributes, and data source. For A and B the ID 001 is an example. The extracted data for the whole dataset (n = 88) is in SupplMat1, 2 and 3.

A. Organización de los datos extraídos de cada artículo acerca de metadatos y contexto geográfico. B. Organización de los datos extraídos de cada artículo acerca del tipo de datos, atributos del bosque seco y fuente de datos. Para A y B, el ID 001 es un ejemplo. Los datos extraídos para todo el conjunto de datos (n = 88) se encuentran en los Materiales Suplementarios 1, 2 y 3.

A

| | Publication meta-data | | | | Geographical context | |
|---|---|---|---|---|---|---|
| ID | Author | Date | Title | Journal | Continent | Geographical unit |
| 001 | Benedictto | 2019 | Structural and Functional characterization of the dry forest in Central Argentine Chaco | Madera y Bosques | South America | Central Argentine Chaco |

B

| ID | Type of data | | Attributes of dry forest | | | Data source | Effectiveness of ecological indicators |
|---|---|---|---|---|---|---|---|
| | RS + FS | RS | Composition | Structure | Functioning | | |
| 001 | X | | species richness, relative abundance, evenness, density | DBH | EVI | MODIS | higher ANPP values with higher density and basal area of trees |

community/ecosystem, (3) landscape/region. Concerning composition indicators, the hierarchy levels of species/population and landscape/region showed the same percentage (42.50 %), followed by ecosystem/community (15.00 %) (table 2). Related to structure indicators, the highest percentages were for species/population (63.41 %) and community/ecosystem (34.15 %) (table 3). For function indicators, the most studied hierarchy level was community/ecosystem (59.76 %), followed by landscape/region (40.24 %), without records at the species/population level (table 4).

In all, 61.36 % of the articles assessed only one of the three ecological attributes. The attributes of function were the most frequently evaluated (42.05 %), followed by structure (14.77 %) and composition (4.55 %) (figure 2). Another 20.45 % assessed two of the three ecological attributes, *i.e.* 9.09 % for structure-function, 6.82 % for composition-function, 4.55 % for composition-structure; and 18.18 % of the articles considered all three ecological attributes (composition-structure-function) (figure 2).

Out of the 88 articles assessed, 47.73 % used remote sensing and field survey data, and 52.27 % used only remote sensing data. When composition attributes were assessed, 31 out of 58 articles (53 %) considered remote sensing data (figure 3); while most of the 38 articles assessing structure attributes used field surveys (n = 25, 66 %) (figure 3). Regarding function attributes, 62 of 65 articles (95 %) considered remote sensing data (figure 3).

Different data sources were used in the dry forest studies selected, 91.77 % were remote sensing data from passive sensors and only 8.23 % were from active sensors. Considering remote sensing data from passive sensors, Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) were the most used (38.62 % and 17.24 % respectively), followed by Digital Elevation Model (DEM) and Google Earth (figure 4). In relation to remote sensing

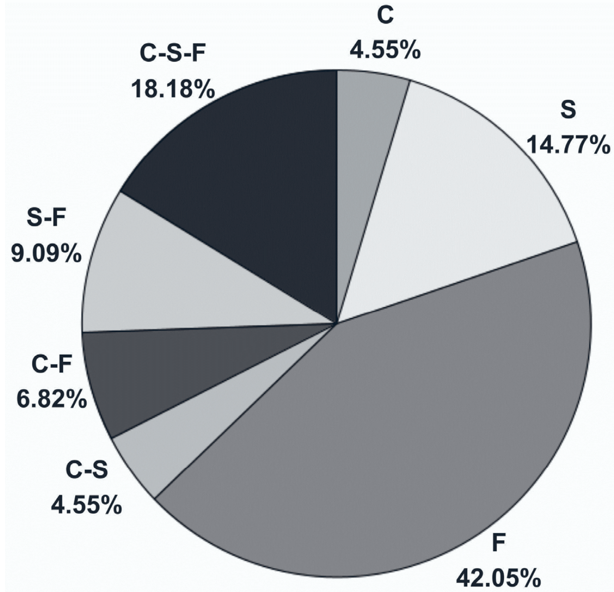


**Figure 2.** Percentage of articles that assess dry forest conditions based on three, two and one ecological attributes. C: composition, S: structure, F: function.

Porcentaje de artículos que evalúan las condiciones del bosque seco en base a tres, dos y un atributo ecológico. C: composición, S: estructura, F: función.

**Table 3.** The structure indicators considered in research articles were classified at the three hierarchy levels. Below each level is the percentage of articles that considered that level for each indicator.

Los indicadores de estructura considerados en los artículos de investigación se clasificaron siguiendo los tres niveles de jerarquía. Debajo de cada nivel se encuentra el porcentaje de artículos que consideraron ese nivel para cada indicador.

| Level hierarchy | Structure |
|---|---|
| Species / population 63.41 % | Diameter at Breast Height (DBH) |
| | Tree height |
| | Density and cover of adult trees |
| | Density of juveniles, seedlings |
| | Stand Basal Area (SBA) |
| Community / ecosystem 34.15 % | Canopy cover/canopy bulk density |
| | Height of stumps |
| | Slope |
| | Aspect |
| | Soil (soil type, edaphic properties, wetness) |
| | Elevation |
| Landscape / region 2.44 % | Landscape metrics: patch composition (type, size, shape) and patch configuration (distance, distribution) |

**Table 4.** The function indicators considered in research articles were classified at the three hierarchy levels. However, we did not have records at the species/population level. Below each level is the percentage of articles that considered that level.

Los indicadores de función considerados en los artículos de investigación se clasificaron siguiendo los tres niveles de jerarquía. Sin embargo, no contamos con registros a nivel de especie/población. Debajo de cada nivel se encuentra el porcentaje de artículos que consideraron ese nivel.

| Level hierarchy | Function |
|---|---|
| Community / ecosystem 59.76 % | Leaf Area Index (LAI) |
| | Plant area index (PAI) |
| | Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) |
| | Evapotranspiration (ET) |
| | Bands: blue, red, Near Infrared (NIR), mid-Infrared (mid-IR) |
| | Normalized Difference Vegetation Index (NDVI) |
| | Enhanced Vegetation Index (EVI) |
| | Soil Adjusted Vegetation Index (SAVI) |
| | Soil Adjusted Total Vegetation Index (SATVI) |
| | Green Vegetation (GV) |
| | Fractional Vegetation Cover (FCOVER) |
| | Non-Photosynthetic Vegetation (NPV) |
| | Difference Vegetation Index (DVI) |
| | Ratio Vegetation Index (RVI) |
| | Wide Dynamic Range Vegetation Index (WDRVI) |
| | Ring-Width Indices (RWI) |
| | Aboveground Net Primary Productivity (ANPP) |
| | Net Primary Productivity (NPP) |
| | Tasseled Cap Transformation (TCT) |
| | Polarization HH, VV, VH |
| | Texture measures (occurrence, co-occurrence) |
| Landscape / region 40.24 % | Anthropogenic disturbances: agriculture, road, human settlements, kiln density, overgrazing, wood extraction/residue, sawing pit. |
| | Disturbance Index |
| | Shortwave radiation (S) |
| | Albedo |
| | Solar Radiation Index (SRI) |
| | Normalized Burn Ratio (NBR) |
| | Surface Temperature (ST) |
| | Solar radiation (SR) |
| | Heat Flux (H) |
| | Latent Heat Flux (LE) |
| | Available Energy (NR-G) |
| | Watercourse |
| | Water Index (WI) |
| | Normalized Difference Water Index (NDWI) |
| | Water vapor air concentrations |
| | Normalized Difference Moisture Index (NDMI) |
| | Topographic Wetness Index(TWI) |
| | Moisture Index (MI) |
| | Soil moisture Index (SWI) |
| | Soil productivity Index |
| | Drought Index (DI) |
| | Groundwater Level (GWL) |
| | Groundwater Depth (GWD) |

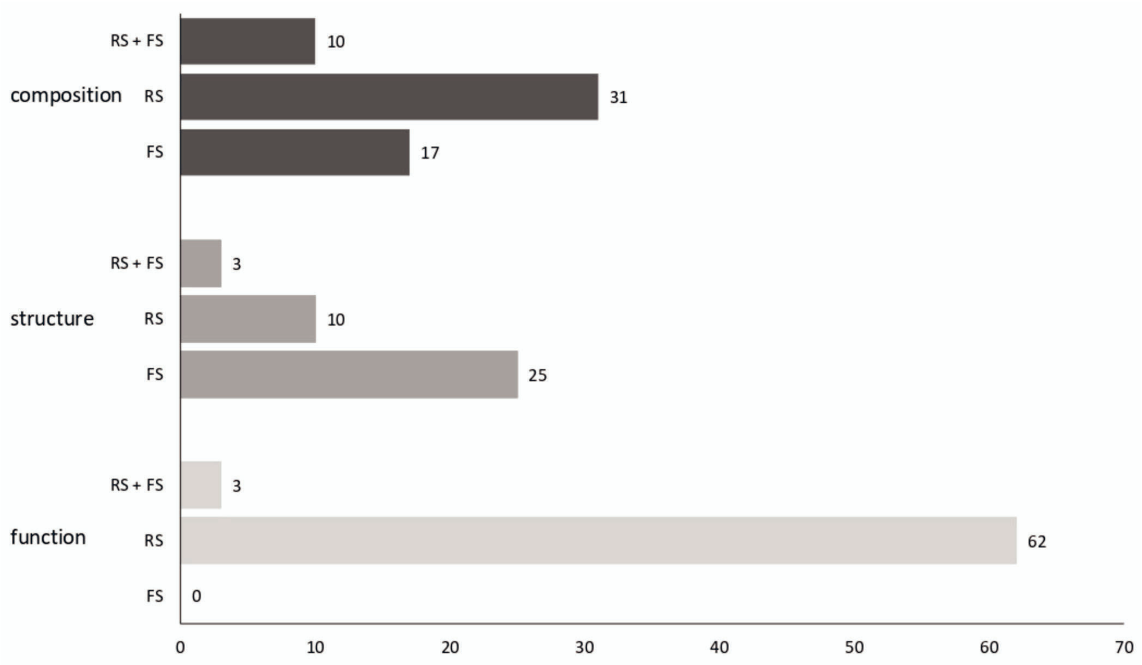


**Figure 3.** Number of articles that considered only remote sensing data (RS), only field survey (FS), or remote sensing and field survey data (RS + FS) for each type of ecological indicator (*i.e.* composition, structure and function).

El número de artículos que consideraron solo datos de sensores remotos (RS), solo estudios de campo (FS) o datos de sensores remotos y estudios de campo (RS + FS) para cada tipo de indicador ecológico (es decir, composición, estructura y función).

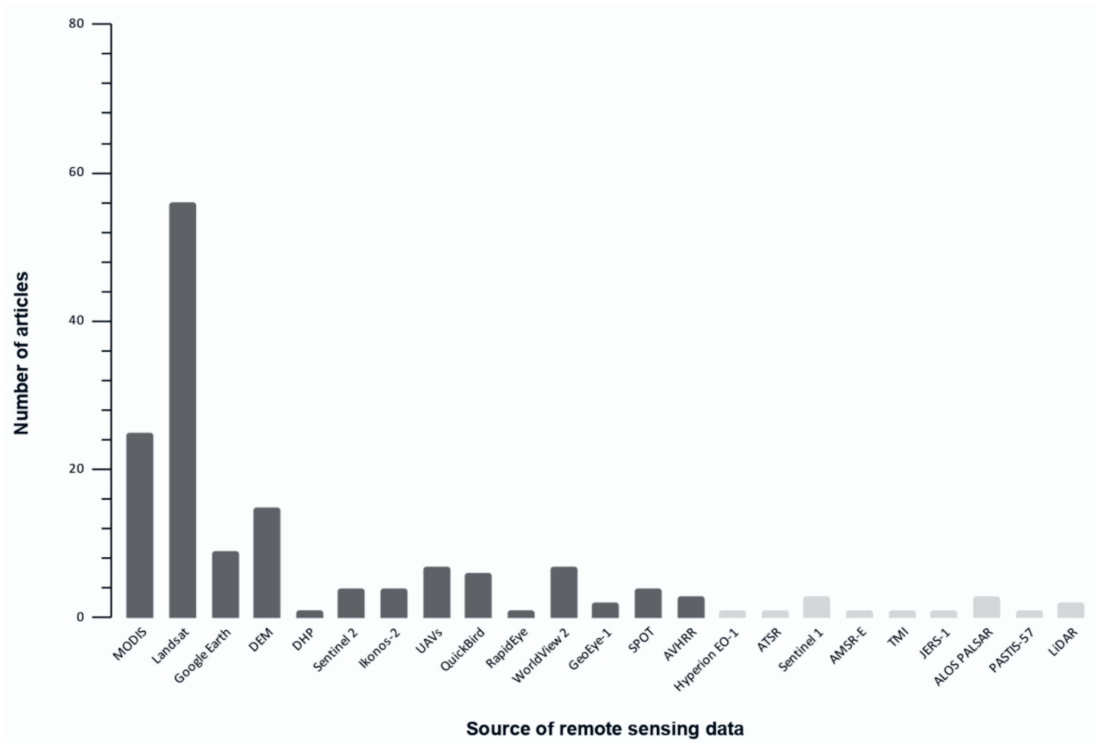


**Figure 4.** Number of articles that used different sources of remote sensing data. The dark gray bars correspond to passive remote sensors, while the light gray bars correspond to active remote sensors.

Número de artículos que utilizaron diferentes fuentes de datos de teledetección. Las barras en gris oscuro corresponden a sensores remotos pasivos, mientras que las barras en gris claro corresponden a sensores remotos activos.

data from active sensors, ALOS Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR) and Sentinel 1 were used with the same frequency (23.08 %), followed by Light Detection and Ranging (LiDAR) (15.38 %, figure 4). The characteristics of different satellites (*i.e.* data source, spatial and temporal resolution, sensor: passive/active, access) are described in table 5. For out of the 88 articles analyzed, 4 report a weak relationship between field surveys and remote sensing data or consider that other less expensive methods are more efficient to assess anthropic disturbance in forests (SupplMat3).

Regarding the geographical distribution of research worldwide, the dry forests of South America were the most studied (46.67 % of articles), followed by Africa (26.67 %), and North America (14.44 %). Dry forests of Asia (6.67 %), Europe (2.22%), and Oceania (3.33 %) were the least studied (figure 5).

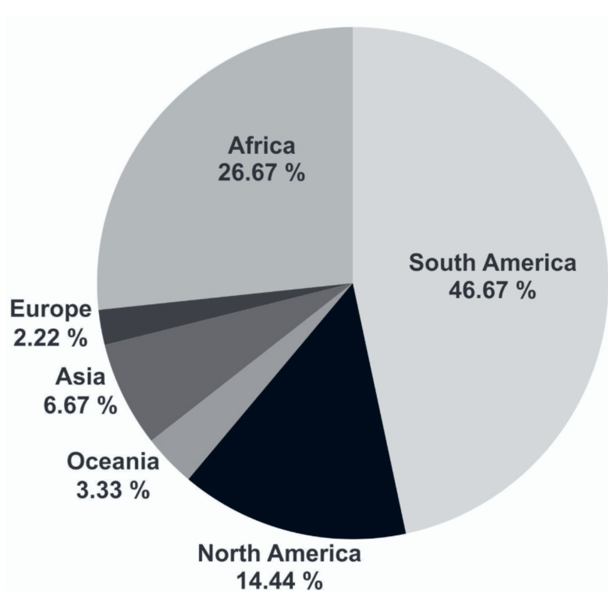


**Figure 5.** Continents studied in the 88 articles included.

Continentes estudiados en los 88 artículos evaluados.

DISCUSSION

Our systematic review showed that most of the 88 articles selected used ecological indicators at species/population and landscape/region hierarchy levels when compositional attributes were assessed, and mainly at the species/population hierarchy level when structural attributes were assessed. Functional attributes were mainly evaluated at the community/ecosystem hierarchy level, followed by the landscape/region level. More than 60 % of the articles considered one of the three ecological attributes, 20.45 % assessed two, and more than 18 % three ecological attributes. When considering type of data (*i.e.* remote sensing data, field survey, or both), over 50 % only used remote sensing data when assessing compositional attributes, and 66 % considered only field survey data when assessing structural attributes. Regarding functional attributes, 95 % used only remote sensing data. More than 90 % of researchers use data from passive remote sensing to evaluate dry forest conditions, with Landsat and MODIS being the most frequently used. Only four articles report a weak relationship between field surveys and remote sensing data or consider another method with low cost. Dry forests of South America were the most studied, followed by dry forests of Africa, and North America.

Ecological indicators have several purposes since they can be used to assess current vegetation conditions, monitor patterns and ecosystem processes, and predict future changes. Moreover, indicators are able to identify the cause of an environmental problem and allow us to quantify its magnitude (Noss 1990). For an accurate assessment, the complexity of ecosystems requires a suite of indicators that represent their three key aspects, *i.e.* composition, structure, and function, always considering that these features can be assessed at various hierarchy levels, from population to landscape (Dale and Beyeler 2001). Our results show that most research assessed one or two ecological attributes, and just over 18 % assessed three ecological attributes. However, the choice of ecological indicators and hierarchy level is not defined only by research objectives, but also involves a combination of appropriate features, costs, and feasibility. The most studied tree genera were *Neltuma* spp. (7 articles) and *Pinus* spp. (4 articles). Most research on *Neltuma* spp. (n = 4) evaluated only functional attributes using remote sensing data. Most research studies on *Pinus* spp., assessed structural and functional attributes by combining remote sensing and field survey data. Particularly, for *Neltuma tamarugo* Phil., remote sensing data has become an important tool to quantitatively assess and monitor its water stress, ranging from experiments to large-scale spatiotemporal studies (Decuyper *et al*. 2016, Chávez *et al*. 2013). Including different hierarchy levels of scaling from leaf traits to canopy structure and regional patterns requires an integrated understanding of plant physiology, ecology, and biogeography with remote sensing data (Farella *et al*. 2022).

The increasing availability of data on drylands ecosystems was enabled by the advent of remote sensing techniques in the 1970s (Smith *et al*. 2019). Remote sensing data is a powerful tool to evaluate current and retrospective conditions of an ecosystem since it allows quantifying and classifying attributes of composition, structure, and function at different hierarchy levels. Until this occurred, drylands had fewer ground observations and research reports than more humid, and typically more developed, areas (Smith *et al.* 2019). Our results showed that composition and function attributes were mainly assessed with remote sensing data, *i.e.* land cover classes (for composition) and through green indices (*i.e.* Normalized Difference Vegetation Index -NDVI-, Enhanced Vegetation Index -EVI-, Soil Adjusted Vegetation Index -SAVI-, Soil Adjus-

**Table 5.** Remote sensing data used in the selected articles: data source, spatial resolution, temporal resolution, sensor (passive/active), free access (indicated with X if remote sensing data is free).

Datos de teledetección utilizados en los artículos seleccionados: fuente de datos, resolución espacial, resolución temporal, sensor (pasivo/activo), libre acceso (indicado con X si los datos de teledetección son gratis).

| Data source | Spatial Resolution | Temporal Resolution | Sensor: passive/active | Free access |
|---|---|---|---|---|
| MOD09A1 (MODIS TERRA) | 500 m | Multi-Day | passive | X |
| MOD11 (MODIS TERRA) | 1,000 m | Daily | passive | X |
| MOD13Q1 (MODIS TERRA) | 250 m | Multi-Day | passive | X |
| MOD13A3 (MODIS TERRA) | 1,000 m | Monthly | passive | X |
| MOD15A2 (MODIS TERRA) | 500 m | Multi-Day | passive | X |
| MOD15LAI (MODIS TERRA) | 500 m | Multi-Day | passive | X |
| MOD16A2 (MODIS TERRA) | 500 m | Multi-Day | passive | X |
| MOD17A (MODIS TERRA) | 500 m | Multi-Day | passive | X |
| MYD04_L2 (MODIS AQUA) | 10,000 m | 5 minute | passive | X |
| MYD05_L2 (MODIS AQUA) | 10,000 m | 5 minute | passive | X |
| MYD06_L2 (MODIS AQUA) | 10,000 m | 5 minute | passive | X |
| MYD07_L2 (MODIS AQUA) | 50,000 m | 5 minute | passive | X |
| MYD11 (MODIS AQUA) | 1,000 m | Daily | passive | X |
| MYD11_A2 (MODIS AQUA) | 1,000 m | Multi-Day | passive | X |
| MYD11_L2 (MODIS AQUA) | 1,000 m | Daily | passive | X |
| MYD13Q1 (MODIS AQUA) | 250 m | Multi-Day | passive | X |
| MCD12C1 (MODIS TERRA/AQUA) | 5,600 m | Yearly | passive | X |
| MCD12Q1 (MODIS TERRA/AQUA) | 500 m | Yearly | passive | X |
| MCD15A2 (MODIS TERRA/AQUA) | 500 m | Multi-Day | passive | X |
| MCD43A2 (MODIS TERRA/AQUA) | 500 m | Daily | passive | X |
| MCD43A3 (MODIS TERRA/AQUA) | 500 m | Daily | passive | X |
| MCD43A4 (MODIS TERRA/AQUA) | 500 m | Daily | passive | X |
| MCD43B2 (MODIS TERRA/AQUA) | 500 m | Daily | passive | X |
| MCD43B3 (MODIS TERRA/AQUA) | 500 m | Daily | passive | X |
| Landsat 5 TM | 30 m | 16 days | passive | X |
| Landsat 7 ETM+ | 30 m | 16 days | passive | X |
| Landsat 8 OLI | 15 m | 16 days | passive | X |
| Google Earth | 15 m-15 cm | | passive | X |
| Digital Elevation Model (DEM) / ASTER | 30 m | | passive | X |
| Digital Elevation Model (DEM) / SRTM | 30 m - 90 m | | passive | X |
| Digital Hemispherical Photography (DHP) | | | passive | X |
| Sentinel 2 | 10 m | 5 days | passive | X |
| Ikonos-2 | 1 m | 3 days | passive | |
| Unmanned Aerial Vehicles (UAVs) | | | passive | |
| QuickBird | 0.6 m | 2 a 12 days | passive | |
| RapidEye | 5 m | Daily | passive | |
| WorldView 2 | 0.46 m | 1.1 day | passive | |
| GeoEye-1 | 0.41 m | 3 days | passive | |

Contiue

Continue Table 5.

| | | | | |
|---|---|---|---|---|
| SPOT | 2.5 m | 2-3 days | passive | X |
| Hyperion sensor satellite EO-1 | 30 m | 16 days | passive | X |
| Advanced Very-High-Resolution Radiometer (AVHRR) | 1 km | daily | active | X |
| Along Track Scanning Radiometer (ATSR) | 1 km | 1 – 3 days | active | X |
| Sentinel 1 | 20 x 22 m | 12 days | active | X |
| Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) | 1,450 km | 2 days | active | X |
| Tropical Microwave Imager (TMI) | 27.75 km | monthly, daily, sub-daily (3hrs) | active | X |
| JERS-1 | 5 - 20 m | 44 days | active | X |
| ALOS PALSAR | 25 m | 46 days | active | X |
| Autonomous System from Transmittance Instantaneous Sensors oriented at 57° (PASTIS-57) | 20 m | 1 to few minutes | active | X |
| Light Detection and Ranging (LiDAR) | 10 m | | active | |

ted Total Vegetation Index -SATVI-), Surface Temperature (ST), anthropogenic disturbances, and Solar radiation (SR), for function attributes. Particularly AGB, is the second indicator most assessed with field survey data, but almost all research studies attempted a good fit with remote sensing data. In general, forests play a vital role in global carbon flux and act as carbon sinks by storing biomass, over a long period of time (Salunkhe *et al*. 2018). For an accurate estimation of biomass based on remote sensing data, it is essential to calibrate and validate this data with field measurements of biomass. According to the fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2007), scarce information is available concerning biomass, and carbon stock/sequestration at national and regional levels. Finding a good adjustment between AGB from field survey data and an indicator obtained from remote sensing data would allow extrapolation to large areas, or at a high hierarchy level (*i.e.* community/ecosystem, landscape/region). Moreover, one of the main advantages of remote sensors is the availability of images with a different temporal resolution that allows monitoring and time-series analyses of vegetation conditions. These multi-time series of remotely sensed vegetation data facilitate our understanding of patterns and processes in dryland ecosystems (Smith *et al*. 2019), in addition to holding promise for future predictions of changes.

Of the 88 articles analyzed, only four report a weak relationship between field surveys and remote sensing data, or consider that other less expensive methods are more efficient for assessing attributes in dry forests. Probably, due to the vegetation conditions in some dry forest areas, it is more effective to use high-resolution images. However, their acquisition cost could be a significant barrier to research in ecology. The selection of images acquired is largely determined by: mapping objective (*i.e.* what to be mapped), cost of images (high-resolution images are very expensive), climate conditions (mainly related to clouds), and the technical issues for image interpretation (related to image quality, preprocessing and interpretation) (Xie *et al*. 2008). From our systematic review it emerges that Landsat and MODIS were the most frequently used sources of satellite imagery of the Earth to evaluate dry forest conditions. Particularly, the Landsat archive with medium spatial resolution provides a history of land surface changes over the last 50 years (since the 1970's decade) through images with different spectral resolutions (Wulder *et al*. 2012). This extensive time series allows us to look at changes over time, which would not be possible even if extensive ground-based monitoring were to begin now. Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) have proven capable of obtaining forest variables both at local and regional scales. Besides, another main advantage of Landsat images is their free availability in comparison with higher resolution images. MODIS (Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard Terra and Aqua satellites. Terra MODIS and Aqua MODIS satellites are together able to record data from the global land surface area with a temporal resolution of 1–2 days, unlike Landsat which has a temporal resolution of 16 days (Gao *et al*. 2020). The images gathered from MODIS are principally used to map changes in the dynamics of vegetation cover and processes. However, unlike Landsat images, mapping at a fine-scale spatial analysis (*i.e.* local or regional) is not recommended with MODIS images due to their coarse spatial resolution (ranging from 250 to 1 km). However, image fusion or combination of MODIS with imagery of higher spatial resolution could lead to achieving more accuracy and precision in mapping results (Xie *et al*. 2008). Another key characteristic to be considered is that, as well as Landsat, images from MODIS are freely available, being an important data resource for assessment and monitoring of dry forest conditions in developing nations, where costs are usually the most important consideration in the development of research.

The Food and Agriculture Organization of the United Nations (FAO) defined forest as "land spanning an area of more than 0.5 ha with a tree cover over 10 % that is not predominantly used for agriculture or urban land use, as well as land on which tree cover is temporarily under 10 % but is expected to recover". Following these parameters, Bastin *et al*. (2017) estimated that Africa is the continent with the largest forest area in drylands (26.56 % of the global dry forest cover), followed by Asia with 19.78 %, North America with 18.94 %, South America with 18.29 %, Oceania with 10.58%, and the lowest for Europe with 5.85 %. According to our results, South America is the continent with the largest number of studies of dry forest conditions with remote sensing data (46.67 %), followed by Africa (26.67 %) and North America (14.44 %). While Africa is the continent with the largest forest area in drylands, it has predominantly open forests (*i.e.* with 10 to 39 % tree canopy cover), unlike South and North America where around 80 % of dry forest areas are closed forests. Dealing with open forests is a significant challenge in remote sensing, especially when compared to closed forests which have more than 40 % tree canopy cover. On the other hand, it is important to highlight that most of the studies of dry forests of South America have used free remote sensing data. Taking into account all articles analyzed, only 27.27 % considered remote sensing data that is not freely available, *i.e.* very high spatial resolution imagery. Each increase in spatial, temporal, and spectral resolution of images, results in an exponential increase in the amount of critical information held in each pixel. However, this higher resolution will most likely increase costs. As claimed by Xie *et al.* (2008) this seems to be an important issue to consider in the process of image selection for research purposes.

Unlike optical sensor images, Synthetic Aperture Radar (SAR) sensors provide information about forest vertical structure or stand volume because they can penetrate the canopy (Zhao *et al*. 2016). They transmit microwave signals and measure the backscattered energy returned from the lighted target, thus allowing obtaining information on land surface features. These sensors show different abilities to penetrate vegetation canopies because they transmit different wavelengths (Flores-Anderson *et al*. 2019). Moreover, SAR images can be acquired day or night, and are not affected by weather conditions, as happens with images from passive sensors (Flores-Anderson *et al*. 2019, Zhu *et al*. 2012). SAR images, in a similar way to optical sensors, allow for continuous and systematic acquisitions of Earth land surface images required to build temporal series. Despite all these advantages, SAR images are infrequently used to assess dry forest attributes. Moreover, observations and products from a single sensor would not be enough to know the conditions of dry forests. Campos and collaborates (2022) found that multi-sensor models that included data from passive (*i.e.* SD of EVI and SAT-VI) and active (*i.e.* VV co-polarisation) remote sensors, showed a higher explained variance (up to 89,6 %) compared with single-sensor models (up to 82,9 %). Pastick and collaborators (2018) using a regression tree modeling approach that combined data from Landsat and Sentinel 2 significantly improved the characterization of dryland phenology. Another promising method is data fusion from multiple sensors, which could be a better integrative analytical technique to represent vegetation dynamics in drylands (Smith *et al*. 2019). Just as it is not recommended to use a single ecological attribute to represent the complexity of these ecosystems, the observations and products from a single sensor often cannot adequately resolve their complex dynamics. The integration of remote sensing data acquired from diverse sensors (*i.e.* passive, active), with diverse spatial and spectral resolution, could enhance our comprehension of dry forest attributes, which still remain in an area of relatively limited knowledge.

## CONCLUSION

Ecosystem integrity assessment refers to system wholeness, including presence of appropriate species, populations, and communities in suitable environmental conditions. This integrity includes assessment of compositional, structural, and functional attributes of ecosystems. Taking this into account satellite remote sensing has been instrumental in the assessment and monitoring of spatial and temporal variations in forest ecosystems. However, dry forest remote sensing has been difficult due to unique challenges such as high soil background reflectance, high spatial heterogeneity and irregular growing seasons, periods of drought, senescent vegetation, with small leaf areas or leafless. In our systematic review, we found that more than 60 % of articles consider only one ecological attribute of dry forest vegetation, with functional attributes being the most assessed with use of remote sensing data. We think that considering only one attribute could lead to a partial understanding of the patterns and processes of that ecosystem. This oversimplification can lead to poor management programs and decisions. A key challenge is to find a group of good indicators able to cover the spectrum of an ecosystem's ecological variations.

Despite being the fourth in dry forest areas, South America is the most studied continent, and most of the studies have used free remote sensing data. In summary, out of the 88 articles analyzed only 27 % of the research works used not-freely-accessible remote-sensing data. We want to stress that availability of free remote-sensing data is a key condition for research development and ecological studies. Free and open access was a true paradigm change toward expanding remote sensing data utilization;

this change improved the depth and scope of the science questions and applications undertaken. Moreover, concurrent with the free and open data policy, the availability of collections and products ready to be used by users improves and reduces time in processing and obtaining research results.

Passive sensors were the most used in the assessment of dry forests, despite active sensors having the potential to advance our current understanding of dryland ecosystems. We considered that future works should be focused on multi-sensor and multi-spatial data*, i.e.* from passive and active sensors, because their combination should be able to identify and quantify different attributes of dry forest ecosystems, from stand scale to landscape.

The gap in the knowledge of dryland remote sensing should be a top research priority since it is necessary to define effective and efficient remote sensing indicators of dry forest conditions. These indicators could be a valuable tool for dry forest management and conservation in different world regions.

## AUTHOR CONTRIBUTIONS

Campos Valeria Evelín: conceptualization; Figueroa Masanet Agostina: data curation; Campos Valeria Evelín and Figueroa Masanet Agostina: formal analysis; Campos Valeria Evelín: funding acquisition, project administration, resources; CamposValeria Evelín: investigation and methodology; Campos Valeria Evelín: supervision; Figueroa Masanet Agostina: visualization, Campos Valeria Evelín: writing original draft; Figueroa Masanet Agostina: writing-review & editing.

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SupplMat1. Publication meta-data and geographical context of the 88 articles included.
Metadatos de publicación y contexto geográfico de los 88 artículos incluidos.

| Publication Meta-Data | | | | | Geographical Context | |
|---|---|---|---|---|---|---|
| ID | Author | Date | Title | Journal | Continent | Geographical Unit |
| 1 | Benedictto | 2019 | Structural and functional characterization of the dry forest in Central Argentine Chaco | Madera y Bosques | South America | Central Argentine Chaco |
| 2 | Cannon | 2020 | Simulating spatial complexity in dry conifer forest restoration: implications for conservation prioritization and scenario evaluation | Landscape Ecology | North America | Montane Forest |
| 3 | Galvíncio | 2013 | LAI Improved to dry forest in semiarid of the Brazil | International Journal of Remote Sensing Applications | South America | Caatinga savannah |
| 4 | Gobbi | 2020 | Comparing Forest Structural Attributes Derived from UAV-Based Point Clouds with Conventional Forest Inventories in the Dry Chaco | Remote Sensing | South America | Dry Chaco |
| 5 | Maldonado-Enríquez | 2020 | Trend and variability of NDVI of the main vegetation types in the Cape Region of Baja California Sur | Revista Mexicana de Biodiversidad | North America | Tropical dry forest |
| 6 | Campos | 2018 | Remote sensing data to assess compositional and structural indicators in dry woodland | Ecological Indicators | South America | Dry forest |
| 7 | Altun | 2008 | Comparing methods for determining forest sites: a case study in Gümüshane-Karanlıkdere forest | European Journal of Forest Research | Europe, Asia | Karanlıkdere Forest District |
| 8 | Andrade | 2020 | Evaluating single and multi-date Landsat classifications of land-cover in a seasonally dry tropical forest | Remote Sensing Applications: Society and Environment | South America | Caatinga forest |
| 9 | Baena | 2017 | Identifying species form the air: UAVs and the very high resolution challenge for plant conservation | Plos One | South America | Forest |
| 10 | Barraza | 2016 | Detection of Trend Change-Point in Passive Microwave and Optical Time Series Using Bayesian Inference over the Dry Chaco Forest | Proceedings | South America | Dry Chaco Forest |
| 11 | Barraza | 2018 | Comparison of the performance of latent heat flux products over southern hemisphere forest ecosystems: estimating latent heat flux eror structure using in situ measurements and the triple collocation method | International Journal of Remote Sensing | South America, Oceania | Dry Chaco Forest and North of the Australia |
| 12 | Bhattarai | 2020 | Assessing spatial patterns of forest degradation in dry Miombo woodland in Southern Tanzania | Cogent Environmental Science | Africa | Miombo woodands |
| 13 | Burry | 2017 | Dynamics of fire, precipitation, vegetation and NDVI in dry forest environments in NW Argentina. Contributions to environmental archaeology | Journal of Archaeological Science: Reports | South America | Dry forest |
| 14 | Carranza | 2014 | Measuring forest fragmentation using multitemporal remotely sensed data: three decades of change in the dry Chaco | European Journal of Remote Sensing | South America | Gran Chaco dry forest |
| 15 | Clark | 2017 | A scalable approach to mapping annual land cover at 250 m using MODIS time series data: A case study in the Dry Chaco ecoregion of South America | Remote Sensing of Environment | South America | Gran Chaco dry forest |

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| 16 | Contreras | 2012 | Abrupt watercourse formation in a semiarid sedimentary landscape of central Argentina: the roles of forest clearing, rainfall variability and seismic activity | Ecohydrology | South America | Espinal (dry forest) |
| 17 | Cunha | 2019 | Surface albedo as a proxy for land-cover clearing in seasonally dry forests: Evidence from the Brazilian Caatinga | Remote Sensing of Environment | South America | Caatinga |
| 18 | Dons | 2014 | Spatial patterns of subsistence extraction of forest products e An indirect approach for estimation of forest degradation in dry forest | Applied Geography | Africa | Miombo woodlands |
| 19 | Drori | 2020 | Precipitation-Sensitive Dynamic Threshold: A New and Simple Method to Detect and Monitor Forest and Woody Vegetation Cover in Sub-Humid to Arid Areas | Letter | Asia | Forest and woody vegetation |
| 20 | Dube | 2016 | Estimating forest standing biomass in savanna woodlands as an indicator of forest productivity using the new generation WorldView-2 sensor | Geocarto International | Africa | Savannah woodlands |
| 21 | Folega | 2014 | Satellite monitoring of land-use and land-cover changes in northern Togo protected areas | Journal of Forestry Research | Africa | Savanna on leached |
| 22 | Forkuor | 2020 | Above-ground biomass mapping in West African dryland forest using Sentinel-1 and 2 datasets - A case study | Remote Sensing of Environment | Africa | Dry forest |
| 23 | Gara | 2015 | Predicting forest carbon stocks from high resolution satellite data in dry forests of Zimbabwe: Exploring the effect of the red edge band in forest carbon stocks estimation | Transactions of The Royal Society of South Africa | Africa | Dry savannah |
| 24 | Gara | 2015 | Indigenous forest wood volume estimation in a dry savanna, Zimbabwe: exploring the performance of high-and-medium spatial resolution multispectral sensors | Geocarto International | Africa | Dry savannah |
| 25 | Gara | 2016 | Estimating forest carbon stocks in tropical dry forests of Zimbabwe: exploring the performance of high and medium spatial-resolution multispectral sensors | Southern Forest | Africa | Dry savannah |
| 26 | Gasparri | 2010 | Assessing multi-temporal Landsat 7 ETM+ images for estimating above-ground biomass in subtropical dry forests of Argentina | Journal of Arid Environments | South America | Gran Chaco dry forest |
| 27 | Gasparri | 2013 | Regional patterns and controls of biomass in semiarid woodlands: lessons from the Northern Argentina Dry Chaco | Regional Environmental Change | South America | Gran Chaco dry forest |
| 28 | Grau | 2008 | Balancing food production and nature conservation in the NeotropicaldryforestsofnorthernArgentina | Global Change Biology | South America | Gran Chaco dry forest |
| 29 | Günlü | 2008 | Classifying Oriental Beech (Fagus orientalis Lipsky) Forest Sites Using Direct, Indirect and Remote Sensing Methods: A Case Study from Turkey | Sensors | Europe, Asia | Forest |
| 30 | Hislop | 2019 | High fire disturbance in forests leads to longer recovery, but varies by forest type | Remote Sensing in Ecology and Conservation | Oceania | Dry forest |
| 31 | Gao | 2020 | Asymmetric impacts of dryness and wetness on tree growth and forest coverage | Agricultural and Forest Meteorology | North America | Arid desert |

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| 32 | Hojdová | 2005 | Microclimate of a peat bog and of the forest in different states of damage in the Šumava National Park | Silva Gabreta | Europe | Dry forest |
| 33 | Houspanossian | 2013 | Radiation budget changes with dry forest clearing in temperate Argentina | Global Change Biology | South America | Dry forest |
| 34 | Hoyos | 2018 | A Multivariate Approach to Study Drivers of Land-Cover Changes through Remote Sensing in the Dry Chaco of Argentina | International Journal of Geo-Information | South America | Gran Chaco dry forest |
| 35 | Liu | 2017 | Vegetation Dynamics in the Upper Guinean Forest Region of West Africa from 2001 to 2015 | Remote Sensing | Africa | Savannah woodlands |
| 36 | Miranda | 2020 | Forest browning trends in response to drought in a highly threatened mediterranean landscape of South America | Ecological Indicators | South America | Savannah and Mediterranian |
| 37 | Marchesini | 2014 | Changes in evapotranspiration and phenology as consequences of shrub removal in dry forests of Central Argentina | Ecohydrology | South America | Gran Chaco dry forest and Monte |
| 38 | Martinez | 2008 | An assessment of Hawaiian dry forest condition with fine resolution remote sensing | Forest Ecology and Management | North America | Dry forest |
| 39 | Mitchard | 2011 | Measuring biomass changes due to woody encroachment and deforestation/degradation in a forest–savanna boundary region of central Africa using multi-temporal L-band radar backscatter | Remote Sensing of Environment | Africa | Forest and Savannah |
| 40 | M'mboroki | 2018 | Climate change impacts detection in dry forested ecosystem as indicatedby vegetationcover change in —Laikipia, of Kenya | Environmental Monitoring and Assessment | Africa | Dry forest |
| 41 | Sun | 2019 | Identification and assessment of the factors driving vegetation degradation/regeneration in drylands using synthetic high spatiotemporal remote sensing Data—A case study in Zhenglanqi, Inner Mongolia, China | Ecological Indicators | Asia | The north is semi-arid and the south is temperate continental monsoon |
| 42 | Monteiro Junior | 2018 | Dynamical spatial modeling to simulate the forest scenario in Brazilian dry forest landscapes | Geology, Ecology, and Landscapes | South America | Caatinga |
| 43 | Nosetto | 2020 | Contrasting CO2 and water vapour fluxes in dry forest and pasture sites of central Argentina | Ecohydrology | South America | Chaco dry forest and Espinal |
| 44 | Powell | 2018 | Characterization of forest carbon stocks at the landscape scale in the Argentine Dry Chaco | Forest Ecology and Management | South America | Chaco dry forest |
| 45 | Quintão de Almeida | 2014 | Empirical relationships between dendrometric characteristics of the Brazilian Caatinga and TM Landsat 5 data | Pesquisa Agropecuária Brasileira | South America | Caatinga |
| 46 | Raymaekers | 2014 | SPOT-VEGETATION GEOV1 biophysical parameters in semi-arid agro-ecosystems | International Journal of Remote Sensing | South America | Chaco Seco Ecoregion |
| 47 | Rueda | 2015 | Charcoal production in the Argentine Dry Chaco: Where, how and who? | Energy for Sustainable Development | South America | Chaco dry forest |
| 48 | Schultz | 2018 | Forest Cover and Vegetation Degradation Detection in the Kavango Zambezi Transfrontier Conservation Area Using BFAST Monitor | Remote Sensing | Africa | Savannah and Dry forest |
| 49 | Sitters | 2011 | Rainfall-Tuned Management Facilitates Dry Forest Recovery | Restoration Ecology | South America | Dry forest |

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| 50 | Walker | 2015 | Phenological Response of an Arizona Dryland Forest to Short-Term Climatic Extremes | Remote Sensing | North America | Dry forest |
| 51 | Zinner | 2013 | Analysis of deforestation patterns in the central Menabe, Madagascar, between 1973 and 2010 | Regional Environmental Change | Africa | Dry forest |
| 52 | Zewdie | 2015 | Remote Sensing based multi-temporal land cover classification and change detection in northwestern Ethiopia | European Journal of Remote Sensing | Africa | Dry forest |
| 53 | Cortés-Ramos | 2020 | Assessment of tropical cyclone damage on dry forests using multispectral remote sensing: The case of Baja California Sur, Mexico | Journal of Arid Environments | North America | Dry forest |
| 54 | Martinez Morales | 2008 | An assessment of Hawaiian dry forest condition with fine resolution remote sensing | Forest Ecology and Management | North America | Dry forest |
| 55 | Bouvet | 2018 | An above-ground biomass map of African savannahs and woodlands at 25 m resolution derived from ALOS PALSAR | Remote Sensing of Environment | Africa | Dry Savannah |
| 56 | Chávez | 2013 | Modelling the spectral response of the desert tree Prosopis tamarugo to waterstress | International Journal of Applie Earth Observation and Geoinformation | South America | Dry forest |
| 57 | Chávez | 2016 | 50 years of water extraction in the Pampa del Tamarugal basin: Can Prosopis tamarugo trees survive in the hyper-arid Atacama Desert (Northern Chile)? | Journal of Arid Environments | South America | Dry forest |
| 58 | Decuyper | 2016 | A multi-scale approach to assess the effect of groundwater extraction on Prosopis tamarugo in the Atacama Desert | Journal of Arid Environments | South America | Dry forest |
| 59 | Ho Tong Minh | 2018 | Potential value of combining ALOS PALSAR and Landsat-derived tree cover data for forest biomass retrieval in Madagascar | Remote Sensing of Environment | Africa | Dry forest |
| 60 | le Polain de Waroux | 2012 | Monitoring degradation in arid and semi-arid forests and woodlands: The case of the argan woodlands (Morocco) | Applied Geography | Africa | Dry forest |
| 61 | Ng | 2016 | MappingProsopisspp. with Landsat 8 data in arid environments: Evaluatingeffectivenessofdifferent methods and temporal imagery selectionfor Hargeisa, Somaliland | International Journal of Applie Earth Observation and Geoinformation | Africa | Dry forest |
| 62 | Rodriguez | 2020 | Changes in water fluxes partition related to the replacement of native dry forests by crops in the Dry Chaco | Journal of Arid Environments | South America | Chaco dry forest |
| 63 | Samara e Silva Medeiros | 2019 | Predicting plant species richness with satellite images in the largest dry forest nucleus in South America | Journal of Arid Environments | South America | Caatinga |
| 64 | Sankey | 2017 | UAV lidar and hyperespectral fusion for forest monitoring in the southwestern USA | Remote sensing of Environment | North America | Dry forest |
| 65 | Schulz | 2010 | Monitoring land cover change of the dryland forest landscape of Central Chile (1975-2008) | Applied Geography | South America | Dry forest |
| 66 | Suganuma | 2006 | Stand biomass estimation method by canopy coverage for application to remote sensing in an arid area of Western Australia | Forest Ecology and Management | Oceania | Dry forest |

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|---|---|---|---|---|---|---|
| 67 | Fontúrbel | 2007 | Evaluación de la pérdida de la cobertura del bosque seco chaqueño en el Municipio de Torotoro y en el Parque Nacional Torotoro (Potosí, Bolivia), mediante teledetección | Ecología Aplicada | South America | Dry forest |
| 68 | Sitters | 2011 | Rainfall-T unedManagementFacilitatesDryForest Recovery | Restoration Ecology | South America | Dry forest |
| 69 | Borak | 2015 | The use of temporal metrics for land cover change detection at coarse spatial scales | International Journal of Remote Sensing | Africa | Dry forest |
| 70 | Bradley | 2006 | Spatial and temporal scale issues in determining biomass burning regimes in Bolivia and Peru | International Journal of Remote Sensing | South America | Dry forest |
| 71 | Mapfumo | 2016 | Detection of subtle deforestation due to logging using satellite remote sensing in wet and dry savanna woodlands of Southern Africa | Geocarto International | Africa | Dry miombo woodlands |
| 72 | Mayaux | 2010 | A near-real time forest-cover map of Madagascar derived from SPOT-4 VEGETATION data | International Journal of Remote Sensing | Africa | Dry woodlands |
| 73 | Mayr | 2017 | Disturbance feedbacks on the height of woody vegetation in a savannah: a multi-plot assessment using an unmanned aerial vehicle (UAV) | International Journal of Remote Sensing | Africa | Dry woodlands |
| 74 | Beuchle | 2015 | Land cover changes in the Brazilian Cerrado and Caatinga biomes from 1990 to 2010 based on a systematic remote sensing sampling approach | Applied Geography | South America | Caatinga |
| 75 | Clark | 2021 | Land change for all municipalities in Latin America and the Caribbean assessed from 250-m MODIS imagery (2001–2010) | Remote Sensing of Environment | South America | Dry forest |
| 76 | Gobbi | 2022 | Forest degradation in the Dry Chaco: A detection based on 3D canopy reconstruction from UAV-SfM techniques | Forest Ecology and Management | South America | Chaco dry forest |
| 77 | Goenaga | 2013 | Unmixing Analysis of a Time Series of Hyperion Images Over the Guánica Dry Forest in Puerto Rico | IEEE Journal of selected topics in applied earth obervations and remote sensing | North America | Dry forest |
| 78 | Grinand | 2013 | Estimating deforestation in tropical humid and dry forests in Madagascar from 2000 to 2010 using multi-date Landsat satellite images and the random forests classifier | Remote Sensing of Environment | Africa | Spiny-dry-forest |
| 79 | Ozdemir | 2011 | Predicting forest structural parameters using the image texture derived from World View-2 multispectral imagery in a dryland forest, Israel | International Journal of Applied Earth Observation and Geoinformation | Asia | Dry forest |
| 80 | Qarallah | 2021 | Evaluating post-fire recovery of Latroon dry forest using Landsat ETM+, unmanned aerial vehicle and field survey data | Journal of Arid Environments | Asia | Dry forest |
| 81 | Queiroga Miranda | 2017 | Reliability of MODIS Evapotranspiration Products for Heterogeneous Dry Forest: A Study Case of Caatinga | Advances in Meteorology | South America | Caatinga |
| 82 | Schneibel | 2017 | Using Annual Landsat Time Series for the Detection of Dry Forest Degradation Processes in South-Central Angola | Remote Sensing | Africa | Miombo woodands |

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|---|---|---|---|---|---|---|
| 83 | Verhegghen | 2022 | Mapping Canopy Cover in African Dry Forests from the Combined Use of Sentinel-1 and Sentinel-2 Data: Application to Tanzania for the Year 2018 | Remote Sensing | Africa | Dry forest |
| 84 | Walker | 2012 | Evaluation of Landsat and MODIS data fusion products for analysis of dryland forest phenology | Remote Sensing of Environment | North America | Dry forest |
| 85 | Walker | 2014 | Dryland vegetation phenology across an elevation gradient in Arizona, USA, investigated with fused MODIS and Landsat data | Remote Sensing of Environment | North America | Dry forest |
| 86 | Wang | 2022 | Disentangling Soil, Shade, and Tree Canopy Contributions to Mixed Satellite Vegetation Indices in a Sparse Dry Forest | Remote Sensing | Ais | Dry forest |
| 87 | Campos | 2020 | Drivers of plant species richness and structure in dry woodland of *Prosopis flexuosa* | Acta Oecologica | South America | Dry forest |
| 88 | Campos | 2022 | Passive and active remote sensing data as indicators of vegetation condition in dry woodland | Journal of the Indian Society of Remote Sensing | South America | Dry forest |

SupplMat2. Type of data, dry forest attributes, and data source of the 88 articles included.

Tipo de datos, atributos del bosque seco y fuente de datos de los 88 artículos incluidos.

| ID | Data | | Attributes of dry forest | | |
|---|---|---|---|---|---|
| | RS + FS | RS | Composition | Structure | Function |
| 1 | X | | tree species identity, species richness, relative abundance, evenness, species density | DBH | EVI |
| 2 | X | | tree species identity | canopy cover, canopy bulk density, tree height | SWI, TWI, SR |
| 3 | | X | | | LAI, FAPAR, NDVI |
| 4 | X | | species richness | DBH, tree height, tree density | |
| 5 | | X | land cover classes | | NDVI |
| 6 | X | | tree species identity, species richness | DBH, tree height, canopy cover | SATVI, texture measures |
| 7 | X | | | tree height, soil conditions | |
| 8 | X | | density, land cover classes | tree height | NDVI |
| 9 | X | | tree species identity, relative abundance, health | canopy cover | GV, NPV |
| 10 | | X | | | EVI |
| 11 | | X | | | ET |
| 12 | X | | AGB, species occurrence, land cover classes | DBH, height of stumps, patches configuration and metrics | anthropogenic disturbances |
| 13 | | X | | | NDVI |
| 14 | | X | land cover classes | | |
| 15 | | X | land cover classes | | NDVI, EVI, bands |
| 16 | | X | land cover classes | | NDVI, watercourse |
| 17 | | X | land cover classes | | albedo, EVI, NDVI, anthropogenic disturbances |
| 18 | X | | land cover classes | | NDVI, anthropogenic disturbances |
| 19 | | X | | | NDVI |
| 20 | X | | AGB, species occurrence, land cover classes | DBH | SR, NDVI, SAVI, bands |
| 21 | | X | land cover classes | | NDVI |
| 22 | X | | land cover classes | DBH | LAI, FCOVER, FAPAR, VV, VH |
| 23 | X | | species occurrence, land cover classes | DBH, tree height | SR, NDVI, SAVI |
| 24 | X | | | DBH, tree height | SR, NDVI, SAVI |
| 25 | X | | species occurrence, land cover classes | DBH, tree height | SR, NDVI, SAVI |
| 26 | X | | AGB, tree volume | | NDVI, SAVI, NDMI |
| 27 | X | | AGB, tree volume, density, land cover classes, wood density | DBH | EVI, NDVI, ST, anthropogenic disturbances |
| 28 | | X | land cover classes | | |
| 29 | X | | tree species identity, land cover classes | soil conditions, altitude, slope, aspect | ST, DI |
| 30 | | X | land cover classes | soil conditions | NBR, ST, DI |
| 31 | X | | tree species identity, land cover classes | | RWI |
| 32 | | X | land cover classes | | ST |

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|---|---|---|---|---|---|
| 33 | | X | | | Albedo, NDVI, ST |
| 34 | | X | land cover classes | soil conditions, altitude, slope, aspect | anthropogenic disturbances |
| 35 | | X | | soil conditions | EVI, NDWI, TCT |
| 36 | X | | Tree species | DBH, canopy cover, elevation | NDVI, TWI |
| 37 | | X | | | albedo, ST, ANPP, ET |
| 38 | X | | species richness, species density | DBH, tree height, canopy cover | |
| 39 | X | | AGB | DBH, tree height | HH, VH |
| 40 | | X | land cover classes | | |
| 41 | X | | land cover classes, AGB | tree height, altitude, slope, aspect | NPP, ST, MI, S |
| 42 | | X | land cover classes | | |
| 43 | | X | | soil conditions | EVI, NDVI, ST, water vapor air concentration, H, LE, NR-G |
| 44 | X | | AGB, wood density, land cover classes | tree height, soil conditions, altitude, slope, aspect | |
| 45 | X | | tree volume | DBH, tree height | NDVI, SR, SAVI |
| 46 | X | | | | LAI, FAPAR, PAI, NDVI |
| 47 | | X | AGB, land cover classes | | anthropogenic disturbances |
| 48 | | X | land cover classes | | SAVI, NDMI |
| 49 | X | | | density and cover of adult trees, juveniles and seedlings | NDVI, TWI |
| 50 | | X | tree species identity | altitude, slope, aspect | NDVI, SR |
| 51 | X | | | DBH | NDVI |
| 52 | | X | land cover classes | | |
| 53 | | X | | | NDVI, EVI |
| 54 | X | | species richness, species density | DBH, tree height, canopy cover | NDVI, texture co-occurrence measures |
| 55 | X | | AGB | tree height, SBA | HH, VH |
| 56 | X | | tree species identity | | LAI, RVI, NDVI, WDRVI, WI, NDWI |
| 57 | | X | tree species identity | | GWD, NDVI |
| 58 | | X | tree species identity | | GWL, NDVI |
| 59 | X | | AGB | DBH | HH, VH |
| 60 | X | | tree species identity, relative abundance, species density | altitude, slope, aspect | SRI, ST, anthropogenic disturbances |
| 61 | | X | tree species identity, land cover classes | | NDVI |
| 62 | | X | | | NDVI, ET |
| 63 | | X | | | SR, NDVI, SAVI, EVI, LAI, NDMI, NDWI, DVI |
| 64 | X | | tree species identity, species occurrence, species density | tree height, canopy cover | |
| 65 | | X | land cover classes | | |
| 66 | X | | tree species identity, species richness | DBH, tree height, canopy area, SBA | LAI |
| 67 | | X | land cover classes | patches configuration and metrics | |

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|---|---|---|---|---|---|
| 68 | X | | species density, cover | | NDVI, TWI |
| 69 | | X | | | NDVI |
| 70 | | X | land cover classes | | |
| 71 | X | | species richness, status | | NDVI |
| 72 | | X | | | NDVI |
| 73 | X | | abundance | | |
| 74 | X | | tree abundance, land cover classes | canopy cover, tree height | |
| 75 | | X | land cover classes | | |
| 76 | | X | | canopy height, tree height | |
| 77 | | X | vegetation cover | | |
| 78 | | X | vegetation cover | | |
| 79 | X | | tree abundance | basal area, stem volume, DBH | |
| 80 | | X | tree abundance, basal area, stem volume, DBH | NBR, gas exchange, leaf and canopy temperature, chlorophyll content | |
| 81 | | X | | | ET |
| 82 | | X | | | disturbance index |
| 83 | | X | tree cover | | |
| 84 | | X | | | NDVI |
| 85 | | X | | | NDVI, EVI |
| 86 | | X | | canopy cover | |
| 87 | X | | richness, abundance of trees | variance in canopy area | SATVI, texture measures |
| 88 | X | | trees and shrubs biomass, abundance of trees | variance in canopy area | SATVI, EVI, VV and VH polarisation |

AGB: Above Ground Biomass, ANPP: Aboveground Net Primary Productivity, DBH: Diameter at Breast Height, DI: Drought Index, DVI: Difference Vegetation Index, ET: Evapotranspiration, EVI: Enhanced Vegetation Index, FCOVER: Fractional Vegetation Cover, FS: Field survey, GV: Green Vegetation, GWD: Groundwater Depth, GWL: Groundwater Level, H: Heat Flux, HH: horizontal-horizontal polarization, LAI: Leaf Area Index, LE: Latent Heat Flux, MI: Moisture Index, NBR: Normalized Burn Ratio, NDMI: Normalized Difference Moisture Index, NDVI: Normalized Difference Vegetation Index, NDWI: Normalized Difference Water Index, NPP: Net Primary Productivity, NPV: Non-Photosynthetic Vegetation, NR-G: Available Energy, PAI: Plant area index, RS: Remote sensing, RVI: Ratio Vegetation Index, RWI: Ring-Width Indices, S: Shortwave radiation, SATVI: Soil Adjusted Total Vegetation Index, SAVI: Soil Adjusted Vegetation Index, SBA: Stand Basal Area, SR: Solar radiation, SRI: Solar Radiation Index, ST: Surface Temperature, SWI: Soil moisture Index, TCT: Tasseled Cap Transformation, TWI: Topographic Wetness Index, VH: vertical-horizontal polarization, VV: vertical-vertical polarization, WDRVI: Wide Dynamic Range Vegetation Index, WI: Water Index.

SupplMat3. Remote sensing data source and effectiveness of ecological indicators of the 88 articles included.

Fuente de los datos de sensores remotos y efectividad de los indicadores ecológicos de los 88 artículos incluidos.

| ID | Remote sensing data source | Effectiveness of ecological indicators | Weak fit / high cost |
|---|---|---|---|
| 1 | MODIS | higher ANPP values with higher density and basal area of trees | |
| 2 | DEM | canopy characteristics coupling with landscape measures | |
| 3 | Ikonos | good fit of models for the LAI values | |
| 4 | UAVs | remote sensing data performance to characterize the undergrowth forest structure is low compared with forest field indicators | X |
| 5 | Landsat | land use and land cover changes | |
| 6 | Landsat | good fit for texture measures of green index and abundance of trees, shrubs, and variance of the canopy area | |
| 7 | DEM, Landsat | weak fit between structure and age forest with productivity | X |
| 8 | Landsat | good fit for the classification of deciduous vegetation with time series | |
| 9 | UAVs, Google Earth, DEM | good fit for very high-resolution images with keystone tree species and their health across wide heterogeneous landscapes | |
| 10 | AMSR-E, TMI, MODIS | good fit combining optical and passive microwave indices to identify events of disturb | |
| 11 | MODIS | good fit for evapotranspiration and remote sensing data | |
| 12 | QuickBird, Landsat | low cost for interviews about anthropic disturb and high cost of remote sensing images | X |
| 13 | MODIS | good fit, to predict and understand the past, between the structure and function of vegetation, precipitation, and fire | |
| 14 | Landsat | good fit between landscape composition and configuration changes with forest fragmentation over time | |
| 15 | MODIS, QuickBird | land use and land cover changes | |
| 16 | MODIS | the roles of forest clearing, rainfall variability, and seismic activity in the formation of abrupt watercourse formation | |
| 17 | Landsat, RapidEye, Google Earth | good fit between surface albedo and land cover clearing from time series | |
| 18 | Landsat, QuickBird, DEM | good fit for spatial patterns of forest degradation with distance to the nearest forest edge or road | |
| 19 | Sentinel 2, Landsat | determination of precipitation-sensitive dynamic threshold to detect forest | |
| 20 | WorldView 2 | dendrometric traits to assess healthy and spatial planning | |
| 21 | Landsat | land use and land cover changes | |
| 22 | Sentinel 1, Sentinel 2, Landsat, DEM | good fit for AGB with stress index and green index | |
| 23 | WorldView 2, GeoEye-1, Landsat | good fit for dendrometric traits (wood volume) with vegetation indices from high spatial resolution images | |
| 24 | WorldView 2 | good fit between forest carbon with vegetation indices derived from high spatial resolution | |
| 25 | WorldView 2, GeoEye-1, Landsat | weak fit between sparsely distributed trees with medium-spatial-resolution sensors | X |
| 26 | Landsat | good fit between AGB with green indexes in the early dry season | |
| 27 | MODIS, Landsat | DBH and human factors control regional patterns of AGB | |
| 28 | Landsat | land use and land cover changes | |
| 29 | Landsat, Quickbird; DEM | good fit between height of dominant trees and productivity | |
| 30 | Landsat, Lidar | good fit between patch and landscape level | |

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|---|---|---|
| 31 | MODIS | good fit between wetness and tree growth |
| 32 | Landsat | good fit between microclimate and healthy forest |
| 33 | MODIS, Google Earth | replacement of dry forests by crops has strong biophysical effects on the energy budget |
| 34 | Landsat | land use and land cover changes |
| 35 | MODIS, Google Earth | human land use and resource extraction were the predominant drivers of vegetation change |
| 36 | MODIS | geographical variation and forest type as indicators of resistance to drought |
| 37 | MODIS, Landsat 5 TM | woody vegetation regulates water dynamics and ecosystem phenology |
| 38 | Ikonos-2, Landsat | quantification of canopy cover to delineate areas for ecological restoration and conservation |
| 39 | JERS-1, ALOS PALSAR, Quickbird, Landsat | AGB predicted by radar in forest-savanna transition areas |
| 40 | Google Earth, Landsat | climate factors, anthropogenic activities, and their interactions defined spatiotemporal variations of vegetation |
| 41 | Landsat, MODIS, Sentinel 2 | good fit between NPP and vegetation degradation |
| 42 | Landsat | simulation of future scenarios of vegetation degradation, taking account land use patterns and coverage |
| 43 | MODIS | patterns of $CO_2$ and water vapor fluxes and their relationships with environmental variables |
| 44 | MODIS, Google Earth | wood density, tree height, and annual carbon as predictors of aboveground biomass, forest stability, and carbon long-term persistence. |
| 45 | Landsat | dendrometric traits (tree diameter and DBH) to assess wood volume |
| 46 | PASTIS-57, DHP, MODIS | indirect validation of classification with remote sensing data |
| 47 | Google Earth | the geographical distribution, and environmental and social context of forest cover/ biomass |
| 48 | Landsat | good fit between tree cover and vegetation density, with green and moisture indexes |
| 49 | Landsat, DEM | long-term effects of seeding and herbivore control in local reforestation projects |
| 50 | Landsat, MODIS, DEM, Google Earth | phenology in response to climate changes |
| 51 | Landsat, DEM | evaluation of forest loss |
| 52 | Landsat, DEM | land use and land cover changes |
| 53 | Landsat, MODIS | land cover classes in response to climate change |
| 54 | Ikonos-2, Landsat | classification object-based is efficient to select areas with a high canopy cover |
| 55 | ALOS PALSAR | good fit between AGB and DBH, tree height and basal area |
| 56 | Scanner | response of canopy reflectance under controlled water stress |
| 57 | Landsat | estimation of canopy growth under water stress |
| 58 | Landsat | estimation of canopy growth under water stress, a multiscale approach |
| 59 | ALOS PALSAR, Landsat 7 | combining radar and optical to estimate forest biomass stocks |
| 60 | DEM, SPOT | monitoring forests using tree density is better than using area |
| 61 | WorldView-2, QuickBird, Landsat, DEM | pixel-based classification is better than object-based classification |

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|---|---|---|
| 62 | MODIS | transpiration in vegetation cover is a good indicator of water vapor flux in the hydrological model |
| 63 | Landsat | spectral variables as indicators of plant species diversity |
| 64 | UAVs, LiDAR | forest classification and individual structural measurements are fundamental for large-scale forest changes |
| 65 | Landsat | land use and land cover changes |
| 66 | Landsat, DEM | good fit between AGB and structure of forest |
| 67 | Landsat | cover forest loss |
| 68 | DEM | vegetation cover in response to climate change |
| 69 | SPOT, Landsat, MODIS, AVHRR | temporal land cover change |
| 70 | ATSR-2, Landsat, AVHRR, SPOT | land cover use land cover change |
| 71 | Landsat, Worldview-2 | good fit between logging and green index |
| 72 | AVHRR, SPOT, Landsat | near-real time mapping and a robust technique for cloud decontamination |
| 73 | UAVs | image based-point cloud has a good fit with plot-scale heights of woody vegetation |
| 74 | Landsat | object-based classification |
| 75 | MODIS | land cover use land cover change |
| 76 | UAVs | vertical integrity and vertical complexity (3D point cloud), canopy height model are good indicators of degradation |
| 77 | Hyperion EO-1 | hyperspectral images assessing seasonal variations of vegetation cover |
| 78 | Landsat | high images resolution of deforestation has low uncertainty |
| 79 | WorldView-2 | good fit between structural forest and texture measures |
| 80 | Landsat, UAVs | remote sensing to estimate physiology of the canopy |
| 81 | MODIS | remote sensing to estimate evapotranspiration |
| 82 | Landsat, DEM, MODIS | time series for the detection of dry forest degradation |
| 83 | Sentinel 1 y 2 | mapping canopy cover with optical and radar sensors |
| 84 | Landsat, MODIS | data fusion of remote sensing data for phenology analysis |
| 85 | Landsat, MODIS | data fusion of remote sensing data for phenology analysis |
| 86 | Landsat, UAVs | good fit between canopy cover and high-resolution multispectral images |
| 87 | Landsat | good fit for structure of woodlands with productivity and exotic mammals |
| 88 | Landsat, Sentinel 1 | good fit for multi-sensor models with trees biomass and abundance, and shrubs biomass |

AMSR-E: Advanced Microwave Scanning Radiometer - Earth Observing System, AVHRR: Advanced Very-High-Resolution Radiometer, DEM: Digital Elevation Model, DHP: Digital Hemispherical Photography, LiDAR: Light Detection and Ranging, MODIS: Moderate Resolution Imaging Spectroradiometer, RS: Remote sensing, TMI: Tropical Microwave Imager, PASTIS-57: Autonomous System from Transmittance Instantaneous Sensors oriented at 57°, UAVs: Unmanned Aerial Vehicles, AGB: Above Ground Biomass, ANPP: Aboveground Net Primary Productivity, DBH: Diameter at Breast Height.