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Modeling vegetation complexity through remote sensing: key concepts and alternative approaches

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Modeling vegetation complexity through remote sensing: key concepts and alternative approaches

Resumen: In this paper, we review the role of remote sensing in the study of vegetation structure and its complexity. Starting from the definitions of vegetation structure and structural complexity, we first analyze concepts related to the application of remote sensing in ecosystem studies. Next, we review the physical foundations of remote sensing, the different types of resolution (spatial, spectral, and temporal) involved in this type of research, and the influence of the instantaneous conditions inherent in data acquisition processes. Additionally, we explore the use of indices that synthesize the information contained in different bands, both those that have been used for many years and others that have been recently developed. The previous sections summarize the knowledge underlying the process of modeling vegetation attributes using remote sensing inputs. In the final section of this paper, we review the two main modeling approaches, namely physical and empirical, contrasting their characteristics, scope, and limitations. Although historically conceived as alternative approaches, there is now a growing trend toward their integration, giving rise to a novel approach known as hybrid modeling. This integration represents a promising strategy that optimizes ecosystem assessment and monitoring, ensuring a balance between efficacy and accuracy in remote sensing-based studies.

Keywords: electromagnetic radiation; empirical modeling; mathematical models; physical modeling; vegetation structural complexity

Modelación de la complejidad de la vegetación a través de percepción remota: conceptos clave y enfoques alternativos

Abstract: En este trabajo revisamos el papel de la teledetección en el estudio de la estructura de la vegetación y su complejidad. Partiendo de las definiciones de estructura de la vegetación y complejidad estructural, en primer lugar, analizamos conceptos relacionados con la aplicación de la teledetección en el estudio de los ecosistemas. A continuación, se revisan las bases físicas de la teledetección, los diferentes tipos de resolución (espacial, espectral y temporal) involucrados en este tipo de estudios, así como la influencia de las condiciones instantáneas inherentes a los procesos de adquisición de datos. Asimismo, exploramos el uso de índices que sintetizan la información contenida en diferentes bandas, tanto los que ya se han utilizado por muchos años como otros de reciente desarrollo. La revisión continúa con el análisis de la textura de las imágenes como una herramienta novedosa para el estudio de las comunidades vegetales. Las secciones anteriores sintetizan el conocimiento que sustenta el proceso de modelación de los atributos de la vegetación a partir de información derivada de la teledetección. En la parte final, se revisan los dos enfoques principales de modelación —el físico y el empírico—, contrastando sus características, alcances y limitaciones. Aunque históricamente concebidos como enfoques alternativos, hoy día existe una tendencia creciente a integrarlos, lo que ha dado lugar a un enfoque novedoso conocido como modelación híbrida. Esta integración representa una estrategia prometedora que permite optimizar la evaluación y el seguimiento de los ecosistemas, garantizando un equilibrio entre eficacia y precisión en este tipo de estudios.

Palabras clave: complejidad estructural de la vegetación; modelación empírica; modelación física; modelos matemáticos; radiación electromagnética

Introducción

Variation and change are pervasive in the natural world. Ecosystem processes and the resulting ecosystem attributes are dynamic and complex due to multiple factors affecting them (Southwood, 1995; Sinclair and Byrom, 2006; Butler and O'Dwyer, 2020). Examples of the most widely studied ecosystem processes are those related to biogeochemical cycles, climate change, primary productivity, and disturbance and ecological succession (Bennett et al., 2009; Harrison et al., 2014; Poorter et al., 2023). The large variability of these processes in all ecosystems worldwide has fostered the development of many methods for their study, as choosing a particular method largely depends on the specific attributes of each system and study goals.

During the last half century, ecosystem science has greatly benefited from the development of remote sensing (Turner et al., 2003; Kuenzer et al., 2011; Wang et al., 2012; Pettorelli et al., 2014). This development has accelerated the emergence and diversification of new approaches to studying vegetation, which is the most conspicuous ecosystem component and, given the comparatively great longevity of plants, particularly of woody species, and their sessility, perhaps the one showing the slowest changes (Mezaal et al., 2017; Einzmann et al., 2021; Ibarra-Manríquez et al., 2022). A major contribution of remote sensing to ecosystem studies has been through the construction of mathematical models aimed at describing, estimating, and predicting ecosystem attributes (e.g., Aschbacher et al., 1995; Ramsey III and Jensen, 1996; Kayitakire et al., 2006; Proisy et al., 2007; Fatoyinbo and Armstrong, 2010; Gallardo-Cruz et al., 2012). Mathematical models are instrumental in explaining ecosystem variability (Hillier and Lieberman, 1990; Cavender-Bares et al., 2022) as they establish quantitative relationships between ecosystem or vegetation properties and a set of external variables provided by remote sensing. Inverse modeling, an alternative process that involves the use of observed data to infer parameters or conditions that best fit the models and allows predicting ecosystem attributes in sites lacking field data (Zhang et al., 2024), is also key to advancing our knowledge of ecosystem dynamics.

Here, we provide an overview of the potential of remote sensing to support efforts of ecosystem attribute modeling, particularly of its plant community component. Our objectives were, (i) to review concepts of vegetation structure and structural complexity, (ii) to summarize advantages and shortcomings of remote sensing inputs and modeling approaches, and (iii) to contrast the empirical vs. physical modeling, and to introduce the hybrid modeling approach based on the combination of these two main approaches. Because the empirical and physical modelling currently represent the two most widely used approaches in remote sensing-based vegetation studies, our review excludes other perspectives such as data fusion (Zhang, 2010; García et al., 2018).

Vegetation structure and structural complexity

Almost three quarters of a century ago, Dansereau (1957) defined vegetation structure as the spatial organization of individuals that constitute a plant community. While spatial organization is undoubtedly a fundamental property of plant communities (Terradas, 2001), it is not the sole structural component. In a broader sense, vegetation structure refers to how these components (i.e., plants) are organized in the three-dimensional space and is primarily defined by their physical and quantitative structure (Kershaw and Looney, 1985; Norman and Campbell, 1989; Meave and Pérez-García, 2013). The physical structure is expressed in two dimensions: the vertical arrangement of plants or their parts, i.e., the distribution of community components along the vertical axis (community's vertical stratification or vertical differentiation), and the horizontal arrangement, which refers to how the components are distributed across the terrain occupied by the community (spatial distribution of species and individuals; Popma et al., 1988; Campbell and Norman, 1989; Bongers, 2001). The quantitative structure relates to the use of numeric variables to evaluate community properties, such as species abundance or basal area (Morin, 1999; Magurran, 2004). Though ideally the study of plant community structure should encompass all its components, including all of them in individual studies is uncommon (Crawley, 1997). The structural component has been the most extensively addressed in vegetation research, particularly in terms of density of individuals or the biomass contributed by each species to the community (quantitative or taxonomic structure; Barbosa et al., 2014; Dube et al., 2016; Zhang et al., 2019). However, significant emphasis has also been placed on quantifying species composition (floristic structure; Mueller-Dombois and Ellenberg, 1974; Kent, 2012).

Related to the concept of community structure is that of structural complexity. Though similar, these two concepts refer to different community attributes. Community structural complexity is more closely related to the variability of its structural components (Cadenasso et al., 2003; LaRue et al., 2019; Lian et al., 2022). Accordingly, a complex community exhibits substantial variation in several dimensions, including biomass, plant height, canopy openness, and their concentration or dispersion in space (McCoy and Bell, 1991). Also, more complex communities tend to host a larger number of species with the concomitant greater diversity of growth forms, crown shapes, trunk diameters (in the case of forest communities), branching patterns, leaf sizes and various functions related to water and carbon economics (Huston, 1994; Bongers, 2001; Mejía-Domínguez et al., 2011; van der Sande et al., 2024). Although one could naturally assume that forests are more complex than non-forest communities, there are examples of the stringing complexity of non-forest vegetation (e.g., Valiente-Banuet et al., 2000).

In addition to the variation of vegetation community attributes through space, these can also be heterogeneous along the temporal dimension. Succession is the ecological process that best allows the observation of changes in vegetation complexity over time (Connell and Slatyer, 1977; Poorter et al., 2024). Through succession, vegetation complexity increases regarding the variability of the physical, taxonomic and floristic structure of the community (Lebrija-Trejos et al., 2011; Anyomi et al., 2022; Poorter et al., 2023).

Remote sensing has transformed the monitoring of biological diversity through structural, compositional, and functional measurements of ecosystems (Turner et al., 2003; Pettorelli et al., 2014; Dube et al., 2016; Cavender-Bares et al., 2022). The use of remote sensing takes advantage of the inherent natural variability of plant communities with different complexity to study them through structural and compositional data (Dronova and Taddeo, 2022), and aims to describe ecosystem states, monitor them over time, and utilize the significance of these variables to build models capable of predicting or estimating structural attributes (Asner et al., 2003; Gallardo-Cruz et al., 2012; Fassnacht et al., 2024). For example, studies of ecological succession can greatly benefit from the use of remote sensing inputs, like LiDAR to assess canopy height development (García et al., 2018), or multispectral imagery to examine phenological patterns using vegetation indices (Manzo-Delgado and Meave, 2003).

Remote sensing in ecosystem and vegetation studies

Since the early second half of the 20th century remote sensing has been an attractive alternative for studying all ecosystems of the planet (Turner et al., 2003; Aplin, 2004; Chuvieco, 2016; Ibarra-Manríquez et al., 2022). At present, most research in this field of study is based on the use of satellite imagery; however, this is by no means the only remote sensing input used in the past or the present to study plant communities (Chinea, 2002; Navulur, 2007; Anderson and Gaston, 2013; Feldman, 2024). For example, aerial photography was widely used prior to the great diversification of sensors mounted on satellite platforms and it is still used in analysis of historical trends of ecosystem changes (Morgan et al., 2010; Chávez et al., 2024). The comparison of aerial photography, satellite imagery, and more recently, UAV (unmanned aerial vehicle) imagery reveals fundamental differences among these remote sensing inputs used in vegetation studies (Feng et al., 2015; Eide et al., 2021; Alvarez-Vanhard et al., 2021; Li et al., 2023). UAV imagery, though capable of greater detail and increasing accessibility, is constrained by its limited coverage area for data acquisition. Conversely, air photographs, but particularly satellite imagery, offer the possibility to cover much larger areas, with different spatial resolutions. In turn, not all satellite imagery is freely available to every user, and despite their prominent role in vegetation monitoring and mapping studies at present (Wulder et al., 2022; Chávez et al., 2024), it is noteworthy that aerial photography continues being part of the remote sensing arena, particularly for precise cartography often linked to forestry (Fleming et al., 2025), and time series reconstruction covering periods predating satellite imagery (Fernández-Pacheco et al., 2023). Although there are different types of remote sensors (e.g., SAR, LiDAR, multispectral, hyperspectral), the following sections will focus mainly on multispectral and hyperspectral.

The physics of the spectral remote sensing

In remote sensing studies based on satellite imagery, all sensors that gather digital information from satellite platforms lie on the same physical principles (Navulur, 2007; Schott, 2007; Knudby, 2021). These principles involve capturing electromagnetic signals reflected by surfaces for the interpretation of the elements present on the terrain, as each material reflects light in a specific way according to its physical and structural properties (Tippens, 2011). Each object has a spectral signature based on how it reflects and emits electromagnetic radiation (Turner et al., 2003; Schowengerdt, 2007). Particularly, in plant community studies, plant reflectance is used in the wavelengths corresponding to the visible portion of the electromagnetic spectrum (red, green, and blue bands), as well as the near and far-infrared regions (Jensen, 2007; Lillesand et al., 2015; Li et al., 2023).

The absorption limit of chlorophyll is in two regions; solar light is strongly absorbed in the blue (490 nm) and red (676 nm) regions, while the green light (554 nm) is little or not absorbed at all, depending on the photosynthetic pigment. In the light received by plants a region known as the red edge, located around 700 nm, is fundamental for remote sensing because this region constitutes an abrupt limit between absorption and reflectance in plants (Delegido et al., 2011; Peña et al., 2019; Zhang et al., 2022; **Fig. 1**). The red edge results from two special optical properties of plant tissues: there is high absorption by chlorophyll in the visible red region, but as the wavelengths slightly increase, reflectance increases rapidly in the near-infrared (Smith et al., 2004; Jones and Vaughan, 2010). This feature has a very important physiological basis: by reflecting the energy at this latter wavelength, plants avoid overheating and the consequent permanent physiological damage. The existence of the red edge provides the basis for vegetation identification and assessment procedures using combinations of red and infrared radiation through indices that will be discussed later (Horler et al., 1983; Bramich et al., 2021).

Like any surface, plants' spectral characteristics can be captured by remote sensors mounted on satellites. Thus, it is possible to establish relationships between the biophysical characteristics of the terrain, and two attributes present in all satellite images: image tone and image texture (Haralick et al., 1973; Haralick, 1979; Strahler et al., 1986; Woodcock and Strahler, 1987). Tone is defined as the mean spectral value captured by the sensor in each pixel and is associated with a reflectance value. Reflectance, in turn, refers to the amount of light reflected per unit area at a specific site (Chinea, 2002). Unlike tone, image texture refers to the spatial arrangement of its pixels and the differences between them in each scene (Haralick, 1979). The use of these variables in vegetation studies has been important to understanding the characteristics of the ecological system studied (Haralick, 1979; Strahler et al., 1986; Shaw and Burke, 2003). Notably, most studies have focused on image tone to analyze the radiometric properties of plant communities (e.g., Schlerf et al., 2005; Ustin and Gamon, 2010; Zhang et al., 2014; Rossi et al., 2021; Feldman, 2024; Kötz et al., 2024), while studies focused on the analysis of texture are still scant but rapidly increasing (e.g., Feng et al., 2015; X. Wang et al., 2023; Du et al., 2024).

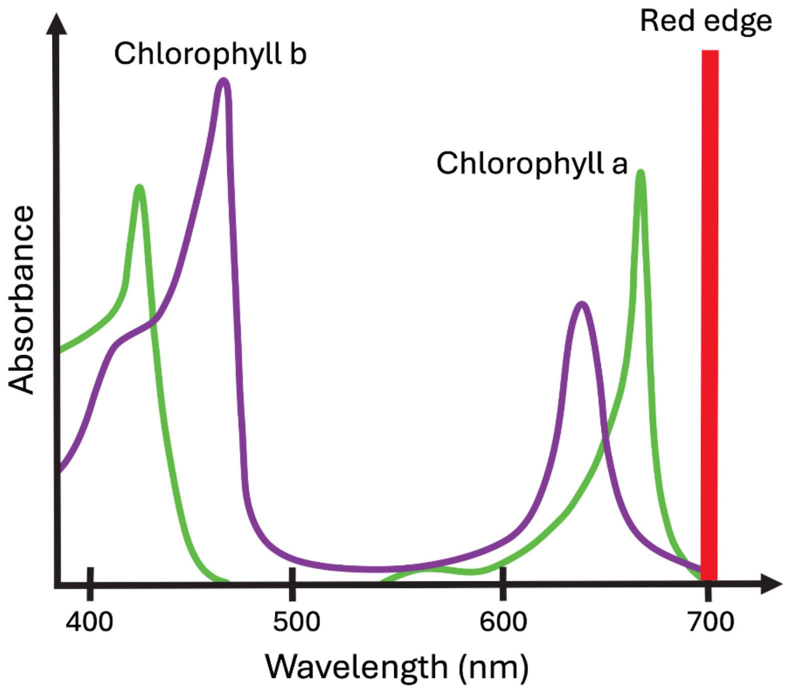

Figure 1. Absorption spectra of chlorophyll a and chlorophyll b in plant tissues. Chlorophyll a (green curve) has absorbance peaks around 430 nm and 665 nm, while chlorophyll b (purple curve) absorbs more efficiently around 455 nm and 640 nm. In remote sensing studies, the sharp transition from high absorbance to high reflectance between the red and near-infrared regions, known as the red edge (approximately around 700 nm and illustrated here as a red bar), was used to construct various vegetation indices relating the reflectance in these regions that provide indicators of photosynthetic activity and vegetation health.

Figura 1. Espectros de absorción de la clorofila a y la clorofila b en tejidos vegetales. La clorofila a (curva verde) presenta picos de absorción alrededor de 430 nm y 665 nm, mientras que la clorofila b (curva morada) absorbe con mayor eficiencia en torno a 455 nm y 640 nm. La transición abrupta de alta absorbancia a alta reflectancia entre el rojo y el infrarrojo cercano, conocida como la pared roja (aproximadamente a los 700 nm e ilustrada aquí como una barra roja), se usó para construir varios índices de vegetación que relacionan la reflectancia en estas regiones y que sirven de indicadores de la actividad fotosintética y la salud de la vegetación.

Resolution of remote sensing inputs

In remote sensing-based vegetation studies, extracting information from satellite imagery hinges on selecting appropriate variables and scales (Woodcock and Strahler, 1987; Guan et al., 2012; Obata et al., 2012; Steenvoorden et al., 2023). Satellite images are characterized by two types of resolution, namely spatial and spectral resolution. In addition, the frequency with which these images are acquired defines their temporal resolution. The three types of resolution, which can be conceived as a spatial-spectral-temporal resolution complex of remote sensing imagery (Q. Wang et al., 2023), are key for interpreting remote sensing data, enabling sensors to capture terrain features ranging from centimeters to thousands of meters, spectral information across various wavelengths (Singh, 1989; Navulur, 2007; Schowengerdt, 2007; Nagendra and Rocchini, 2008), and ecological processes occurring over different time periods (Willis, 2015).

Spatial resolution is the smallest discernible visualization of an object in an image (Atkinson and Aplin, 2004) and allows appreciating the variation of the objects contained in it (Strahler et al., 1986; Foody et al., 2001; Nagendra and Rocchini, 2008; Wang et al., 2010). Pixels are squared units of an image containing a fraction of the radiometric information reflected by the surface and their size determines their capacity to detect the details of the spatial elements on the terrain (Atkinson and Aplin, 2004; Leduc and Knudby, 2018; Lyu et al., 2022). Pixel size defines such level of detail and varies depending on the sensors' detection capabilities. Navulur (2007) proposed four resolution categories according to pixel size: (i) low resolution, with pixels > 30 m; (ii) medium resolution, > 2 to ≤ 30 m; (iii) high resolution, 0.5 - 2 m; and (iv) very high resolution, < 0.5 m. Although remote sensing studies have used images of all four resolution categories, high and very high spatial resolutions are commonly used in current environmental research because they increase precision in identifying and characterizing small objects on the ground (Nagendra and Rocchini, 2008; Wolter et al., 2009; Wang et al., 2010; Myint et al., 2011; Morin et al., 2019; Ahmad et al., 2021). For example, the larger the area to be studied, the lower the spatial resolution tends to be. Similarly, band width in the electromagnetic spectrum captured by a sensor determines its ability to detect spectral differences and constitutes the spectral resolution of the images, which leads to their classification as multispectral or hyperspectral. In turn, temporal resolution refers to the frequency of observations of the same event over time in the same area (Navulur, 2007; Schowengerdt, 2007). These events can be short-lived (such as fires or hurricanes) or processes that require annual assessments (e.g., successional changes in vegetation cover, urban growth, etc.). Although temporal resolution is not a property of the images themselves, it is directly related to the different interpretations of ecological processes recorded in the images. When vegetation monitoring is planned to be conducted over long time periods, it is important to decide the most adequate temporal resolution. For example, the study of a long-term successional process may only require one or few images per year, whereas the analysis of the leaf flushing periods in a deciduous community could need daily images to capture the detailed dynamics of this process.

An important issue in selecting the most appropriate resolutions (i.e., spatial, spectral, and temporal) for a given study is the existence of trade-offs among these resolutions, which explains why there is no perfect high-resolution sensor in all its components (**Fig. 2**). The trade-off between spatial and spectral resolution is particularly critical. For example, hyperspectral images provide a very high level of detail in spectral information, with over one hundred continuous spectral bands (Shaw and Burke, 2003; Xie et al., 2008) and thus can be used for highly specific purposes, such as determining the spectral signature of species present in an ecosystem (Blasco et al., 1998; Hossain and Lin, 2003; Adam et al., 2009); however, they lack the ability to capture finer elements in the landscape. By contrast, multispectral images are composed of up to twelve spectral bands, which means that they only contain specific regions of the electromagnetic spectrum (Asner and Heidebrecht, 2002; Adam et al., 2009), but their spatial resolution is higher, better able to capture more detailed elements on the ground (**Fig. 2**).

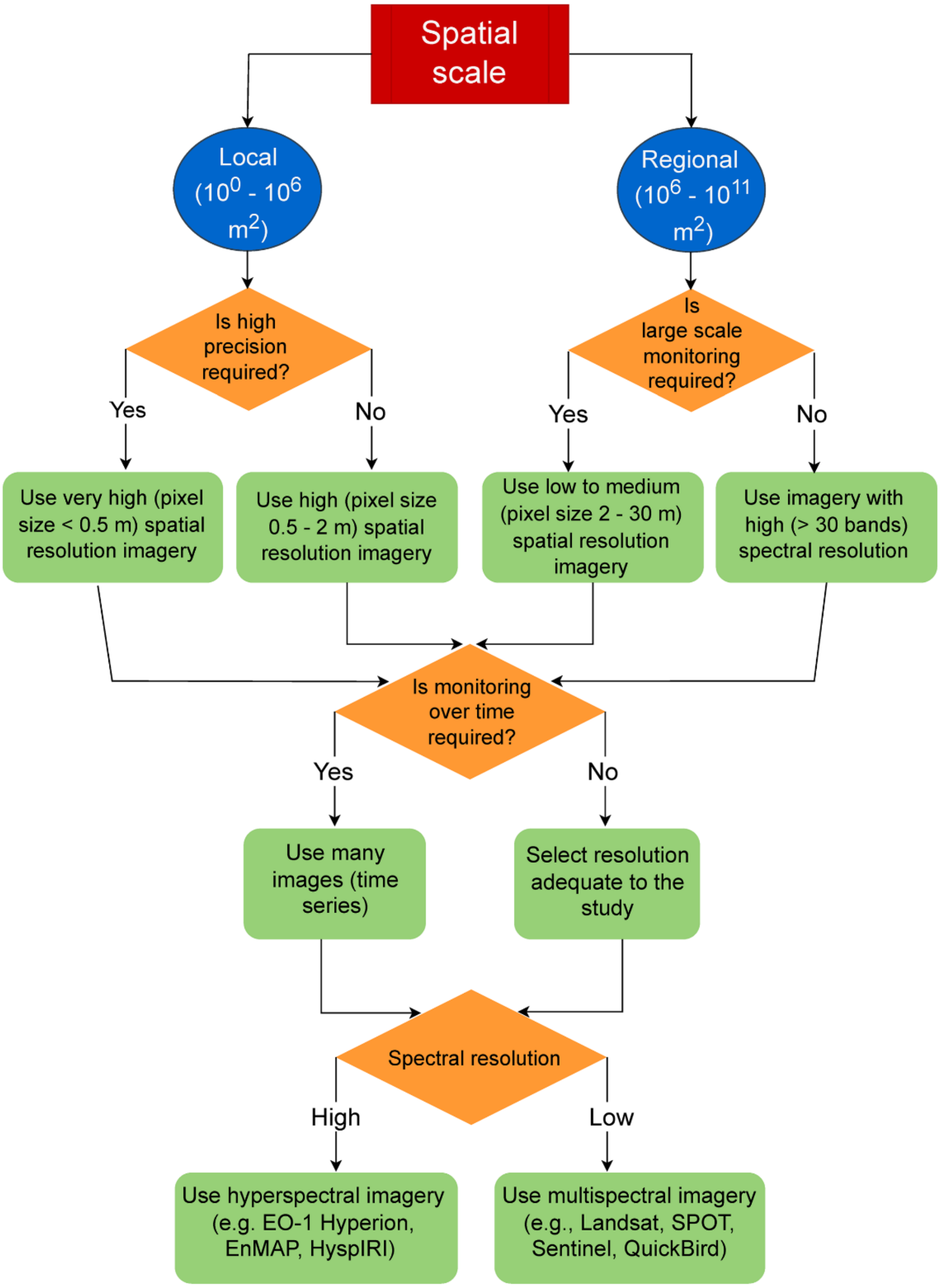

Figure 2. Flowchart for guiding the selection of remote sensing imagery based on spatial scale, required precision, the need for temporal monitoring, and spectral resolution. Different levels of spatial and spectral resolution must be considered to optimize information analysis according to the study objectives. The ranges of areas corresponding to the local and regional scales are based on Turner and Gardner (2015). High precision refers to the degree of detail required in the study. Large scale monitoring refers to a large areal coverage of the study.

Figura 2. Diagrama de flujo para guiar la selección de imágenes de teledetección en función de la escala espacial, la precisión requerida, la necesidad de monitoreo temporal y la resolución espectral. Se deben considerar distintos niveles de resolución espacial y espectral para optimizar el análisis de la información según los objetivos del estudio. Los intervalos de las áreas que corresponden a las escalas local y regional se basan en Turner y Gardner (2015). El término alta precisión se refiere al grado de detalle requerido en el estudio. Monitoreo de gran escala se refiere a una cobertura grande del área de estudio.

One dilemma faced by vegetation studies using classical remote sensing is the selection of inputs for analysis. Ideally, their spatial and spectral resolutions, along with the temporal resolution of the study, should match the particularities of the studied phenomenon. For one, the best spatial resolution is one that precisely matches the size of the study object (Strahler et al., 1986; Woodcock and Strahler, 1987; Nagendra and Rocchini, 2008); for example, in studying a highly complex plant community, using a very high spatial resolution may be advisable, so that the heterogeneity observed in the image pixels can be explained by the heterogeneity of the plant community components. By contrast, if the spatial resolution is considerably higher than the objects being studied, most measurements in the image will be strongly autocorrelated, and the measurement of local variance will decrease (Strahler et al., 1986; Woodcock and Strahler, 1987). In turn, if the study focuses on a community composed by a large number of species, hyperspectral images are recommended because they can effectively capture the variation in their radiometric signals (Kothari and Schweiger, 2022; Zahra et al., 2024). Therefore, depending on the community attribute being assessed, different types of satellite images can be used.

The influence of instantaneous conditions during image capture

An inherent challenge in studying phenomena on the Earth's surface from the distance is the interference that occurs during the capture of spectral data in a satellite image (Adjovu et al., 2023; Fichot et al., 2023). Generally, image quality is affected by the interference derived from the physical characteristics of the atmosphere and the surface at the moment of its capture. The behavior of light waves is highly variable, and there are factors that directly or indirectly interfere with the scattering, absorption, and reflection of signals (Tippens, 2011).

The first difficulty faced by remote sensors mounted on satellite platforms is the large distance for detecting radiometric signals. The Earth's atmosphere reduces the amount of electromagnetic energy reaching the sensor as it disperses and absorbs part of the original signal (Myneni et al., 1995; Chinea, 2002; Chuvieco, 2016). However, the atmosphere is not the only source of interference. Other factors, such as local topography, can create deformations in the image or cast shadows that modify radiometric signal values. The angle of the sun relative to the zenith and the sensor's viewing angle are also closely related (Singh, 1989; Shepherd and Dymond, 2003; Yin et al., 2022). Spectral values vary depending on the time of image acquisition: capturing an image when the sensor or the sun is at the zenith is different from doing so when either one has a degree of inclination, potentially resulting in the recording of different spectral values (Shaw and Burke, 2003). Despite the development of sun-synchronic sensors that control the relationship between the angle at which the sun illuminates the scene and the angle with which the sensor records the image (Shepherd and Dymond, 2003; Wei et al., 2011), these remain major obstacles that typically arise at the moment of capturing the image. Moreover, in the case of topography, it is impossible to have control over it (Dozier et al., 2022).

Fortunately, at present there are procedures available that correct or minimize these effects, including radiometric, topographic, and atmospheric corrections. The topographic correction does not allow correcting topographic shadows; instead, it focuses on adjusting the image's geometry to align it correctly with the Earth's surface (Shepherd and Dymond, 2003; Yin et al., 2022). In turn, the radiometric and atmospheric corrections enable the transformation of reflectance values to physical units at various levels (Wulder et al., 2019; Dozier et al., 2022). Together, these actions make up the image pre-processing phase, which is intended to make the images more suitable for extracting information related to variables that describe the surface (Navulur, 2007).

Remote sensing indices

The tone of the pixels contained in digital images can be used in plant community studies through its incorporation in algorithms known as spectral indices, which relate the electromagnetic energy reflected by the vegetation (and its physical conditions) with the energy detected by remote sensors. Indices are arithmetic combinations of the band channels of an image (Camps-Valls et al., 2012) and their construction is based on the relationships between these bands, which allows for a better assessment of biophysical phenomena in the field. The motivation for the construction of these indices was the need to deal with the interference of physical factors such as soil reflectance, solar illumination, atmospheric conditions, and sensor viewing geometry in detecting spectral values of objects on a given surface with remote sensors (Jensen, 1983; Camps-Valls et al., 2012).

Based on plants' spectral characteristics, specialized indices have been constructed to study vegetation (Navulur, 2007; West et al., 2019; Zhang et al., 2022; Ståhl et al., 2024). Most vegetation indices currently used can differentiate vegetation from other cover types. This is achieved thanks to the pigments contained in the leaves of plants, in addition to the detection of spectral signatures characteristic of each cover type (Iqbal et al., 2021). The Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) are among the most widely used indices for vegetation monitoring and assessment (Tucker et al., 1985; Gao, 1996; Huete et al., 1997; Blasco et al., 1998; Wang et al., 2010), as they can provide relevant information about its condition at a given time, or to predict attributes such as biomass, structure, and species richness. The design of these indices took advantage of the specific reflectance and absorbance properties of plant pigments (Sinclair et al., 1973; Tucker and Sellers, 1986; Hosgood and Jacquemoud, 1994). The main difference between NDVI and EVI is that the latter reduces the saturation of canopy variations under high photosynthetic activity, thus remaining sensitive to canopy variations, while NDVI does present saturation (Huete, 1988; Huete et al., 1997; Vogelmann et al., 1993). In turn, the Soil-Adjusted Vegetation Index (SAVI) incorporates an adjusted soil constant to minimize the effect of bare soil reflectance in the scene (Huete, 1988), making it a more refined or better-calibrated index. The Normalized Difference Water Index (NDWI) provides a consistent framework for analyzing vegetation health regardless of variations in sensor and illumination conditions while distinguishing water bodies from vegetation and soil (Gao, 1996).

With the development of new sensors with higher spectral resolution (e.g., Sentinel-2), novel indices have been developed to take advantage of these new capabilities, such as indices including the red-edge and narrow NIR (e.g, NDVIre1(Gitelson and Merzlyak, 1994), NDVIre2, NDVIre1n, and NDVIre2n (Fernández-Manso, 2016), Plant Senescence Reflectance Index (PSRI; Merzlyak et al., 1999); Chlorophyll Index Red-edge (CIre)). For example, the Red-Edge Normalized Difference Vegetation Index (NDVIre), which reduces sensitivity to foliage density and detects subtle variations in vegetation health that NDVI may miss. Additionally, NDVIre is more sensitive to chlorophyll concentration and reduces the saturation issues in regions with dense biomass (Zhang et al., 2022). In turn, CIre is more closely related to chlorophyll content in comparison with other vegetation indices (Gitelson et al., 2003). Other indices have been developed to monitor photosynthetic activity, such as the photochemical reflectance index (PRI; Gamon et al., 1992) or the chlorophyll/carotenoid index (CCI; Gamon et al., 2016). See Zeng et al. (2022) for a detailed review of spectral indices.

Implementing any vegetation index requires spectral transformations of the information collected by remote sensors, specifically converting the digital numbers (as recorded in the spectral bands) into reflectance values (Xue and Su, 2017). Such transformation is essential because normalized reflectance values enable consistent comparison of data from different images and sensors; in addition, it allows compensation for variations in illumination conditions and sensor characteristics, thus ensuring that the calculated vegetation indices are accurate and useful for analyzing vegetation health (Perry Jr and Lautenschlager, 1984).

Using texture in assessing plant communities

In addition to studying plant communities based on the analysis of their reflectance, a new approach has emerged in ecology that consists in relating the spatial (and spectral) characteristics of pixels with the variation of structural attributes of plant communities (e.g., Smith and Baker, 1978; Tucker, 1979; Huete, 1988; Foody et al., 2001; Couteron et al., 2002, 2005; Proisy et al., 2007, 2011; Ploton, 2010; Fatoyinbo, 2010; Gallardo-Cruz et al., 2012; Ploton et al., 2012, 2013; Barbier and Couteron, 2015; Block et al., 2016; Tompalski et al., 2016; Solórzano et al., 2017). These analyses, known as textural analyses, represent a more complex approach than the sole analysis of reflectance, as they focus on the differences in reflectance between two or more adjacent pixels (Haralick et al., 1973; Haralick, 1979), and aim to relate their arrangement in the image to the spatial configuration of the studied plant community and its characteristics on the ground. There are various methods for analyzing texture, such as the Gray-Level Co-occurrence Matrix (GLCM), and the Fourier Transform and Orthogonal Transform (FOTO) (Kiltie et al., 1995; Clausi and Zhao, 2002; Proisy et al., 2007, Bastin et al., 2014; Singh et al., 2014; Ploton et al., 2017; Solórzano et al., 2018). With this approach, it is possible to describe and predict vegetation attributes such as biomass, stem density, basal area, and overall vegetation structure (Ohmann and Gregory, 2002; Couteron et al., 2005; Satyanarayana et al., 2011; Proisy et al., 2011; Tompalski et al., 2016; Solórzano et al., 2017; Lalechère et al., 2024). Landscape heterogeneity plays a key role in detecting textural patterns in the image, and in the use of remote sensing to estimate community attributes (Farwell et al., 2021). For example, on heterogeneous terrain, the image will reflect certain spatial characteristics associated with landscape conditions (higher or lower density, canopy openness, presence of areas without apparent vegetation, and differences in tones of vegetation cover; Parker et al., 2019; Daleo et al., 2023). Image texture can be used to assess similarities in specific regions of the same image (Gallardo-Cruz et al., 2012). The ability to distinguish specific elements within an image depends on its spatial resolution: the higher the spatial resolution, the greater the level of detail reflecting the elements within the depicted space (Wang et al., 2022).

Although texture analyses tend to be especially useful in modeling structural attributes, it remains unclear which metrics are more relevant since their performance depends on the resolution of the images used, the geometry determining the scene acquisition and illumination, the vegetation attribute and the vegetation type being studied, as well as the vegetation's phenological condition during the image acquisition (Aquino et al., 2025; Bruniquel-Pinel and Gastellu-Etchegorry, 1998; Culbert et al., 2009; Liu et al., 2024; Lu and Batistella, 2005; Solórzano et al., 2017; Gallardo-Cruz et al., 2024). Nonetheless, statistical metrics (e.g., GLCM mean, GLCM var and GLCM correlation) and those summarizing tone variation among contiguous pixels (e.g., GLCM contrast, GLCM homogeneity, and GLCM entropy) are frequently part of the GLCM variables included in the best-performing models (Kayitakire et al., 2006; Eckert, 2012; Gallardo-Cruz et al., 2012; Liu et al., 2024; Solórzano et al., 2017; Solórzano et al., 2018; Ozdemir and Karnieli, 2011) or the ones capturing the dominant texture pattern (e.g., FOTO PC1 and FOTO PC2; Bastin et al., 2014; Couteron et al., 2005; Ploton et al., 2017; Proisy et al., 2011). Although the use of texture metrics for modeling vegetation attributes primarily falls within the empirical framework, there is significant potential to examine it through physical modeling or a hybrid approach (e.g., Bruniquel-Pinel and Gastellu-Etchegorry, 1998; Wan et al., 2019).

Modeling based on remote sensing inputs

The use of spectral attributes of plant communities has proven effective for assessing and monitoring vegetation, which is particularly important in the context of rapid land use change involving vegetation degradation or complete clearance (Lausch et al., 2018; Steinbach et al., 2023). A growing trend in remote sensing-based vegetation studies is the application of diverse approaches of mathematical modeling. These methods include simple correlations, linear and non-linear regressions, and more complex techniques such as machine learning algorithms (e.g., random forests, support vector machines, Extreme Gradient Boosting), as well as deep learning methods for more advanced modeling (Ma et al., 2019; Tassi and Vizzari, 2020; Islam et al., 2023; Lin et al., 2023; Shafi et al., 2023; Zaka and Samat, 2024). These techniques allow making more accurate and efficient analysis of vegetation changes, helping address the growing need for effective monitoring of ecosystems.

Mathematical models can relate ecosystem attributes to the information obtained from remote sensors to explain environmental variations (e.g., Proisy et al., 2007; Gallardo-Cruz et al., 2012; Block et al., 2016; Solórzano et al., 2017). These models must be adjusted and made increasingly more refined to increase their ability to describe environmental variations. To this end, there must be a strong correspondence between the related variables so that the fitted models can explain a substantial portion of reality. To ensure that this requirement is met, it is important to construct a sufficiently large number of models to be tested, along with subsequent modifications (Hillier and Lieberman, 1990; Proisy et al., 2007).

The development of a mathematical model involves conducting exhaustive tests to identify and correct as many issues as possible in order to increase its reliability (Sargent, 2010). The process of testing and improving a model to increase its validity is known as model validation, which can reveal areas where the model has shortcomings and requires modification. Ultimately, model construction requires determining the interpretation, description, or prediction capabilities of the different models, as well as their ability to generalize results and their sensitivity to capturing specific information (for example, the presence or concentration of chlorophyll in the specific case of vegetation indices) (Shehadeh et al., 2021). Some decades ago, Hillier and Lieberman (1990) proposed a systematic approach to test a specific model using a retrospective test, where historical data were used to determine if the model and the resulting solution perform well. Currently, validation tests do not normally use data from the past; rather, they are typically based on data that have not been exposed during the model fitting or training phases (Piirainen et al., 2023; Stock, 2025).

Ideally, one of the most desirable validation strategies would be to validate with independent field plots, once the model has been fitted. This approach has the advantage of randomly distributing new points throughout the entire study area and covering the full range of modeled values. However, this route is frequently unrealistic to accomplish due to economic and time restraints; thus, other more pragmatic strategies have been proposed.

When research often faces limitations regarding data set size (e.g., due to the difficulty to obtain field data, time and budget restrictions, etc.), cross-validation is a good alternative (Zhang and Wang, 2010; Yates et al., 2023). Cross-validation is an iterative process consisting in the creation of all possible training sets while leaving out a given amount of data. Examples of these are the leave-one-out, leave-two-out cross-validations, or v-fold cross-validation, all of which involve splitting the data into two sets, namely the validation and the training set (the latter containing one or two data points; Bürkner et al., 2021). By making this distinction between the two sets and using an iterative process, the goal is to predict the validation set using the model fitted with the training set. Cross-validation allows evaluating the reliability of predictive models when tested on unvisited sites to estimate specific parameters of these sites (Tredennick et al., 2021).

Other approaches consider that predictive and predicted variables are often spatially autocorrelated (Legendre, 1993). Thus, other validation strategies, such as spatial, buffer and environmental blocks, have emphasized the need to consider the spatial configuration of the data to properly evaluate the predictive potential of the fitted models (Valavi et al., 2019). Under these approaches, the training and validation datasets are spatially structured, providing deeper insights into whether the model can be effectively generalized to data that are both similar or different from the training data (Roberts et al., 2017). The main advantage of this strategy is that the undermining spatial autocorrelation of the data is integrated into the validation process.

In remote sensing-based vegetation studies, transformations are often used to standardize image data and mitigate undesired effects related to the immediate elements of image capture (Jensen, 2007), as transformations ensure value consistency and reduce interference. However, data transformations can introduce errors that may be magnified due to the nature of the transformation itself (Lillesand et al., 2015), potentially leading to conclusions considered ecological fallacies (Pollet et al., 2015). Although transforming the data may be necessary to adjust them to known distributions, this may not be advisable if the data are manageable in their original scale, or when they are insufficient or have evident quality issues (Borgonovo et al., 2014; Lee, 2020).

Physical modeling vs. empirical modeling: Alternative approaches for studying ecosystem processes

From the perspective of remote sensing, two main modeling approaches may be distinguished, which are respectively known as empirical modeling and physical modeling (**Table 1**). Empirical modeling aims to establish direct relationships between a given surface and the spectral data obtained from an image of the same area. In other words, the field data are fitted to descriptive and predictive models that in theory represent some observed characteristic. Although empirical models only incorporate a few features of the system being described, they have allowed the construction of relationships that adequately explain the processes occurring on the surface (Thakur, 1991; Myneni et al., 1995; Blasco et al., 1998; Ramsey et al., 1998). Despite this ability, however, empirical models lack the necessary information and theoretical background to precisely express the type of existing relationship or its nature. In other words, with this approach it is difficult to determine the processes and mechanisms involved in the observed results.

The use of empirical models has been highly effective in studying spatial, spectral, and radiometric characteristics of the surface based on remote sensing imagery (Kenneth-Shultis and Myneni, 1988), as it allows assessing the correspondence between ecosystems and their optical information, facilitating speedy explanations of the behavior of some attributes with promising results (e.g., Couteron et al., 2005; Kayitakire et al., 2006; Proisy et al., 2007; Fatoyinbo et al., 2008; Fatoyinbo and Armstrong, 2010). Estimating community biomass, modeling its structure, density, and richness, as well as delineating its extent and vegetation vigor, are among the most sought-after objectives of this approach (Proisy et al., 2011; Barbier et al., 2012; Gallardo-Cruz et al., 2012; Block et al., 2016). Although empirical modeling began to develop since the emergence of remote sensing and has been widely used, some factors limit its accuracy. One of them (and perhaps the most questioned) is its space-time dependency (Strahler et al., 1986): empirical models depend on specific atmospheric conditions and the exact moment at which the data were captured by remote sensors (Kirk, 1984; Chinea, 2002).

Naturally, physical conditions vary from one moment to the next; variables such as the sun's inclination relative to the sensors, atmospheric light scattering, cloud cover, topographic shadow, time of day, position of the sun in the sky, humidity conditions, etc., are major factors that often interfere with the quality of the signal captured by remote sensors (Singh, 1989). Such interference poses difficulties in building general models that aim to represent a significant fraction of the variability present on the terrain when changing location, season, or time, even for the same vegetation type. Despite these shortcomings, empirical modeling has proven very useful for evaluating, mapping, and delimiting processes such as fires or changes in vegetation cover (Foody, 2003; Margules and Sarkar, 2009; Ustin and Gamon, 2010). Undoubtedly, the use of empirical models has significantly reduced study time and costs, while enabling timely decision-making in ecosystem management (**Fig. 3**; **Table 1**; Shaw and Burke, 2003; Turner et al., 2003; Aplin, 2004; Xie et al., 2008; Wang et al., 2010).

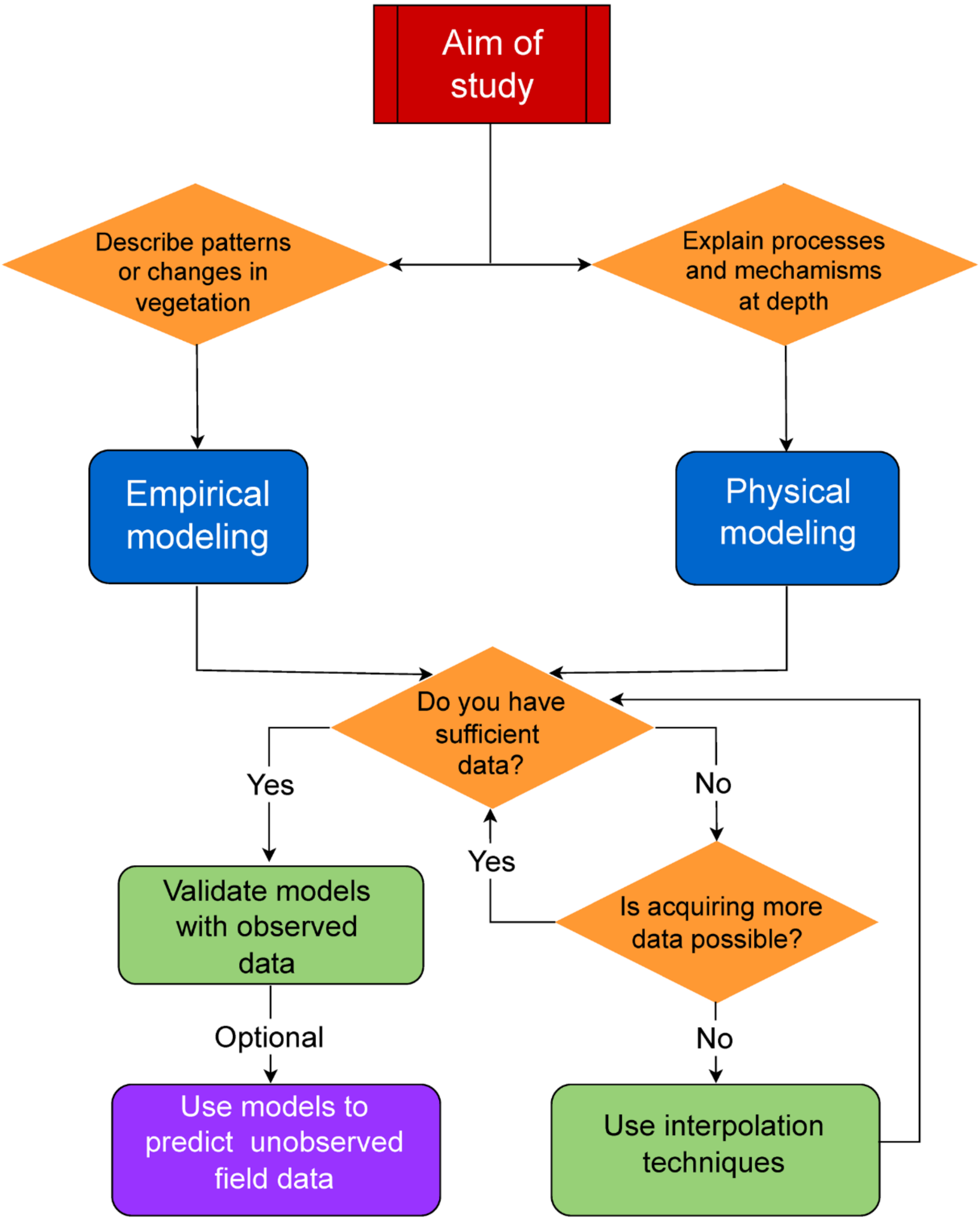

Figure 3. Flowchart for guiding the selection of the modeling approach in remote sensing-based vegetation studies. Two main approaches are distinguished: empirical modeling, aimed at describing patterns and changes in vegetation, and physical modeling, focused on explaining processes and mechanisms in depth. The choice depends mostly on the study goals, the availability of field data and the possibility of acquiring additional information. Interpolations techniques refer to the use of algorithms to estimate intermediate unobserved values between two observed values.

Figura 3. Diagrama de flujo para guiar la selección del enfoque de modelado en estudios de vegetación basados en teledetección. Se distinguen dos enfoques principales: modelado empírico, orientado a describir patrones y cambios en la vegetación, y modelado físico, enfocado en explicar procesos y mecanismos en profundidad. La elección depende fundamentalmente de los objeticos del estudio, la disponibilidad de datos de campo y la posibilidad de adquirir información adicional. Las técnicas de interpolación se refieren al uso de algoritmos para estimar valores intermedios no observados entre dos valores observados.

Table 1. Comparison of the characteristics, aims, strengths and weaknesses of the empirical and physical modeling approaches in remote sensing-based ecosystem studies.

Tabla 1. Comparación de las características, objetivos, fortalezas y debilidades de los enfoques empírico y físico de modelación en estudios de ecosistemas basados en la teledetección.

Characteristics	Empirical modeling	Physical modeling
Details needed	General studies: no detailed information from the study site is required	Detailed knowledge about the physical properties of the materials and their interactions with radiation is required
Complexity of implementation	Relatively easy to implement; standard computing requirements	Higher level of complexity and high computational requirements are needed to achieve precise results
Sensitivity to acquisition conditions	High temporal dependency on instantaneous conditions at the moment of image acquisition	Independence from instantaneous conditions at the moment of image acquisition
Generalization capacity	Limited generalization; mostly valid for the same or a similar study system	High generalization; may be applied to different conditions thus facilitating extrapolation to different environments
Data acquisition effort	Rapid acquisition of useful data for different objectives (generally mapping, assessment, and monitoring)	Acquisition of the necessary information to build the models is time consuming and cumbersome
Mechanistic understanding	The underlying mechanism of the model is unknown or unimportant	Understanding the underlying mechanism of the model is key
Dependency on training data	Highly dependent on training data; insufficient data cause reduced model performance	Lower dependency; these models can be calibrated with observed data, a process that is not comparable with training
Model adaptability	High adaptability; empirical models can be used in different sites and conditions with greater confidence	Limited adaptability; model parameters require adjustments to use it in different sites and conditions
Current level of use	Widely used in remote sensing-based vegetation studies	Still infrequently used in remote sensing-based vegetation studies
Scalability	High scalability; empirical models can be used across scales without strong restrictions.	Low scalability; physical models can only by used under the same conditions in which they were constructed.

Recognition of the limitations of empirical modeling led to the development of an alternative modeling approach known as physical modeling, which involves the construction of theoretical models based on the physical attributes of ecosystem features (**Table 1**). These theoretical models aim to understand as deeply as possible the nature of sources of radiation and their interaction with the environment (Sinclair et al., 1973; Myneni, 1991; Jacquemoud et al., 2000; Jiao et al., 2024). For this reason, the construction of physical models requires large amounts of specific data on variables that allow relating the physical characteristics of the system to its electromagnetic signals (Allen et al., 1969). Ultimately, the purpose of physical modeling is to produce detailed and specific knowledge of the modeled variables, as well as to establish causal relationships that explain the variation of ecosystem processes with the highest possible accuracy (Abdoun and El-Sekelly, 2017). In the case of plant communities, studies based on physical modeling consider multiple characteristics such as the spatial distribution of plants, their reflectance, illumination conditions, transmittance, absorption, and scattering of photons or electromagnetic waves, internal leaf tissue structure, the nature and concentration of pigments, chloroplast density, biochemical composition, and water content, among many others (Sinclair et al., 1973; Hosgood and Jacquemoud, 1994; Feldman, 2024).

Despite their importance for analyzing ecosystem processes, the development of physical models has not been limited to the study of plant communities but is also applied in other fields of knowledge, for example geology, civil engineering, and mining (Abdoun and El-Sekelly, 2017). All these types of studies explore elementary (static) processes on the surface to fully understand their characteristics and interactions, as well as to develop strategies for better understanding the observed phenomena. While these two goals may be achieved based on the same physical principles, it must be noted that modeling the surface for material identification is not comparable to modeling an ecological process (Kennedy et al., 2020). The latter involves highly dynamic relationships between variables that interact with each other, such as seasonality or humidity. These relationships increase the intrinsic complexity of the process and make it highly variable over short time intervals.

Notwithstanding their complexity, physical models offer attractive advantages over empirical models. For example, understanding the variation of the reflectance of a surface in relation to the terrain's geometry can be done by simulating the interaction of light with the atmosphere and vegetation, a task that is accomplished by the DART (Discrete Anisotropic Radiative Transfer) model and the Bidirectional Reflectance Distribution Function (BRDF) (Gerard and North, 1997; Gastellu-Etchegorry et al., 2004). A further major advantage of physical modeling is its spatio-temporal independence; in this regard, a well-developed, highly complex physical model has the potential to build regional models applicable under different circumstances. Of course, integrating all the knowledge thus acquired involves a high degree of complexity (Prakash et al., 2017). Furthermore, having a large amount of detailed information does not guarantee success in modeling a process. Overall, physical modeling increases precision and the ability to describe a phenomenon in detail, but requires specific resources (materials and instruments) to study the modeled variables more deeply. Additionally, the possibility to fully comprehend the interactions among model variables requires solid theoretical knowledge. For these reasons, the choice of the most useful approach to study ecosystem processes depends on the level of detail and scales involved (Woodcock and Strahler, 1987).

The comparison of the advantages and shortcomings of the two modeling approaches reviewed here explains why determining which is the best route for studying ecosystem processes is not straightforward. In fact, to consider the use of one or the other, it is necessary to have basic information about the system, its components, and its possible responses. Despite its limitations, empirical modeling has a proven ability to address problems that arise in parallel to the study of ecosystems. Furthermore, empirical models tackle the problem from a more practical perspective, focusing on modeling vegetation and its attributes without the necessity to understand the underlying mechanisms. By contrast, physical modeling aims for a more precise understanding of each variable considered, and, by doing so, it sheds light on the mechanisms involved in the terrain-image interactions by studying specific variables. Nevertheless, this is a time-consuming process, which represents a disadvantage in view of the accelerated deterioration of ecosystems and their processes, which requires immediate attention.

It has been suggested that physical modeling could eventually replace empirical modeling (e.g., Abdoun and El-Sekelly, 2017), but this claim may be unfounded as it overlooks important considerations related to the study of ecosystems. Although the examination of the main characteristics that distinguish the empirical and physical modeling approaches suggests that they are mutually exclusive, that is, that researchers should opt for one or the other in their studies, we envision a high potential to their combined use in remote sensing-based vegetation studies. On the one hand, both approaches can be conceived as complementary, since empirical modeling can contribute with case studies and identify research gaps, while physical modeling can provide the physical basis to understand the differences detected in these cases and facilitate a unifying comprehension. On the other hand, the combined application of the two modeling approaches can increase the precision of the predictions of vegetation attributes, which appears to be particularly effective in regions fraught with data scarcity (Zhou et al., 2023; Liu et al., 2025; Kumar et al., 2024). The integration of the two approaches has given rise to the emergence of a novel approach known as hybrid modeling (Schweidtmann et al., 2024).

Hybrid modeling takes advantage of the characteristics defining each approach synthesized in Table 1 and increases the explanatory capacity of the models through training processes, when using, for example, Machine Learning, while minimizing the limitations of each model taken individually (Zhou et al., 2023; Jiao et al., 2024). For example, the increased modeling precision associated to the physical approach may be offset by its high computational requirements and higher costs (Liu et al., 2025). In turn, empirical models are admittedly less precise, but they offer a much higher generalization potential in addition to their higher accessibility to many users due to its simplicity. In constructing physical models, the calculation of some parameters can be mathematically very complex, and in these cases, they may be replaced by coefficients obtained through empirical modeling. Likewise, empirical models could be used to fit the residuals of the physical models, which could result in physically sound models, but having higher predictive capacity and generalization potential than each of these models separately. However, the benefits from using a hybrid approach must not be overstated, as its inadequate use, for example, when the physical modeling component is not based on a sound knowledge of the physical nature of the studied elements, may result in reduced explanatory potential and modeling precision (Schweidtmann et al., 2024).

Conclusions

Several decades have elapsed since the introduction of remote sensing in ecosystem studies; however, innovations are still arising, offering new ways to understand the natural world and its processes. The two main approaches for modeling ecological attributes and processes through remote sensing (namely, empirical and physical modeling) contrasted in the last section of this review have different aims and neither one is superior nor more useful than the other. As is the case when selecting a given image spatial or spectral resolution, choosing a certain modeling approach for a remote sensing study always involves a trade-off between data precision and the efficiency in the use of resources, including time and data processing capabilities. Undoubtedly, studies focused on monitoring the spatial distribution of vegetation attributes and their changes over time, mostly conducted with an empirical approach, are invaluable from a practical perspective. On the contrary, physical modeling is rather geared toward gaining a deeper understanding of the relationship between surface properties, illumination characteristics, and remote-sensed variables. More importantly, however, it is increasingly evident that these approaches are not mutually exclusive, as it combined use (represented by the emergent hybrid modeling approach) makes the most of each of them while overcoming some of their drawbacks, all of which results in much more precise and efficient modeling. By viewing the two approaches as complementary research tools, we may be better able to address pressing needs in ecosystem monitoring. Of course, the future development of hybrid modeling faces important challenges, and future research avenues should focus on issues such as the feasibility of scaling hybrid models, or their transferability across ecosystems.

Data and code availability

This paper does not use original datasets.

Authors' contributions

Daniel Chávez: Conceptualization, investigation, writing-first draft, writing-review and editing. **Jonatan V. Solórzano**: Investigation, writing-review and editing. **Jorge A. Meave**: Conceptualization, investigation, writing-review and editing.

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