



APPROACHES, POTENTIAL, AND CHALLENGES IN THE USE OF REMOTE SENSING TO STUDY MANGROVE AND OTHER TROPICAL WETLAND FORESTS

DANIEL CHÁVEZ^{1,4}, JORGE LÓPEZ-PORTILLO², J. ALBERTO GALLARDO-CRUZ³, JORGE A. MEAVE^{1*}

¹ Departamento de Ecología y Recursos Naturales, Facultad de Ciencias, Universidad Nacional Autónoma de México, Mexico City, Mexico.

² Red de Ecología Funcional, Instituto de Ecología A.C., Xalapa, Veracruz, Mexico.

³ Centro Transdisciplinario Universitario para la Sustentabilidad, Universidad Iberoamericana Ciudad de México, Mexico City, Mexico.

⁴ Posgrado en Ciencias Biológicas, Universidad Nacional Autónoma de México, Mexico City, Mexico.

*Author for correspondence: jorge.meave@ciencias.unam.mx

Abstract

Tropical wetland forests are fragile ecosystems facing critical risks due to global warming and other anthropogenic threats. Hence, gathering accurate and reliable information on them is urgent. Although remote sensing has demonstrated great potential in studying terrestrial ecosystems, remote sensing-based wetland forest research is still in an early stage of development. Mapping wetland forests, particularly mangrove forests, was an initial goal of this approach and is a task that still faces methodological challenges. Initially based on aerial photography only, wetland forest mapping through remote sensing underwent explosive diversification after the launching of artificial satellites in the 1970s. Later, precision in wetland forest mapping increased with the combination of hyperspectral, multispectral, and high and very high-resolution imagery. Accurate delimitation of wetland forest extent is also necessary to assess their temporal dynamics (losses, gains, and horizontal displacement). Despite the prevalence of mapping studies, current remote sensing-based research on wetland forests addresses new questions and novel aims, such as describing and predicting wetland forest attributes through mathematical modeling. Although this approach has made substantial progress in recent decades, modeling and predicting wetland forest attributes remain insufficiently explored fields of research. Combining active and passive sensors is a promising alternative to provide a more accurate picture of these communities' attributes. In particular, LiDAR and radar-based technologies may help overcome difficulties encountered in older studies. In the future, we will witness conceptual and methodological progress that will enable us to surmount the remaining challenges.

Keywords: active sensors, passive sensors, prediction of community attributes, vegetation mapping, vegetation monitoring, vegetation structure.

Resumen

Los humedales arbóreos tropicales están críticamente amenazados por el calentamiento global y otras amenazas antropogénicas; por ello, urge recopilar información confiable sobre estas comunidades vegetales. Aunque la percepción remota ha demostrado gran potencial en el estudio de ecosistemas terrestres, la investigación de los humedales arbóreos con este enfoque requiere mayor desarrollo. El mapeo de los humedales arbóreos (particularmente manglares), que fue el objetivo inicial de este enfoque, aún enfrenta desafíos metodológicos. Inicialmente basado solo en fotografías aéreas, el mapeo de humedales arbóreos se diversificó explosivamente con el lanzamiento de satélites artificiales y la interpretación de imágenes de percepción remota. La precisión de los mapas de estas comunidades aumentó con el uso combinado de imágenes multi-espectrales, hiperespectrales, de alta y muy alta resolución. Para evaluar la dinámica temporal (pérdidas, ganancias, desplazamiento horizontal) de los humedales arbóreos necesitamos delimitar de manera precisa su extensión. Aunque todavía se están cartografiando numerosos humedales arbóreos, la investigación actual de estos ecosistemas por percepción remota aborda nuevas preguntas y objetivos (*e.g.*, predecir los atributos comunitarios por medio de modelos matemáticos). A pesar de sustanciales avances recientes, el modelado y la predicción de los atributos de los humedales arbóreos siguen siendo temas poco explorados. La combinación de sensores activos y pasivos es una alternativa promisoriosa para evaluar con precisión los atributos de estas comunidades, y las tecnologías de radar y LiDAR pueden ayudar a superar dificultades enfrentadas en el pasado. Los avances conceptuales y metodológicos en el futuro permitirán superar los desafíos que aún persisten.

Palabras clave: estructura de la vegetación, mapeo de la vegetación, monitoreo de la vegetación, predicción de atributos comunitarios, sensores activos, sensores pasivos



The quantitative study of ecosystems provides essential information for their thorough understanding and proper management and conservation (Seppelt *et al.* 2011, Viani *et al.* 2017, Valtonen *et al.* 2021). Nonetheless, current knowledge about practically every ecosystem on Earth is far from satisfactory. An attractive alternative to advance in this regard is offered by remote sensing, a highly relevant science that studies the biophysical features of the terrain through the analysis of data acquired by remote sensors (Chinaea 2002, Turner *et al.* 2003, Aplin 2004, Navulur 2007, Schowengerdt 2007, Mabwoga & Thukral 2014, Valderrama-Landeros *et al.* 2018, Chuvieco 2020). Remote sensing has fostered the study of ecosystems mainly by focusing on their plant cover, which is their most conspicuous component (Rasolofoharinoro *et al.* 1998, Hansen *et al.* 2013, Mezaal *et al.* 2017, Abdel-Hamid *et al.* 2018, Einzmann *et al.* 2021). Numerous studies on various aspects of the planet's vegetation through remote sensing have demonstrated the great potential of this discipline to identify, map and monitor plant communities and their attributes without having direct contact with the terrain (Chinaea 2002, Aplin 2004, Xie *et al.* 2008, Wang *et al.* 2010, Hansen *et al.* 2013, Mabwoga & Thukral 2014, Song *et al.* 2016, Putut Ash Shidiq *et al.* 2017, Islam & Ma 2018, Einzmann *et al.* 2021).

Wetlands are among the most important and, at the same time, most critically endangered ecosystems of the world (Valiela *et al.* 2001, Islam 2010, Islam *et al.* 2014, Mabwoga & Thukral 2014, Al-Naimi *et al.* 2016, Mao *et al.* 2021). Climate change seriously threatens their persistence, and multiple human activities strongly impact them (Kovacs *et al.* 2009, Lee *et al.* 2014, Islam *et al.* 2014, Thomas *et al.* 2017, Cho & Qi 2023). Given the physical characteristics of their habitats and the peculiarities of the vegetation typical of these ecosystems, access to them is difficult, mainly when they cover extensive areas (Kuenzer *et al.* 2011, Sharma 2018). This difficulty explains to some extent the relatively low pace at which crucial information on their structure, composition, and conservation status is gathered; this is worrisome given their high rates of transformation and fast disappearance (López-Portillo & Ezcurra 2002, Flores Mejía *et al.* 2010, Hogarth 2007, Landgrave & Moreno-Casasola 2012, Steinbach *et al.* 2023). An additional property of wetland ecosystems is the high variation of their vegetation; from a practical perspective, such variation can be reduced to the distinction between those communities dominated by herbs (herbaceous wetlands) and those in which dominance is shared by several woody species (wetland forests; [Figure 1](#)), among which mangrove forests have received the most attention from vegetation ecologists (Moreno-Casasola *et al.* 2009, Infante Mata *et al.* 2011).

In recent decades, remote sensing has been increasingly used in the study of mangroves and other tropical wetland forests (*e.g.*, Aschbacher *et al.* 1995, Proisy *et al.* 2000, Couteron *et al.* 2005, Fatoyinbo & Armstrong 2010, Solórzano *et al.* 2018). Most studies have been based on the analysis of vegetation reflectance to delineate their spatial distribution and temporal dynamics (Huete 1988, Gao 1996, Foody *et al.* 2001, Foody 2003, Lu *et al.* 2004, Kuenzer *et al.* 2011, Valderrama-Landeros *et al.* 2018), while other aspects, for example, their internal structure, have received less attention. In this paper, we provide an overview of the different goals pursued and achievements in studying tropical wetland forests through remote sensing. The review compares conceptual and methodological approaches, whose variety has resulted in a broad gamut of information that would probably not exist without the available theoretical framework and analytical tools. The initial sections provide a brief synopsis of tropical wetland forests to clearly define the object of this review and a historical overview of the development of remote sensing-based wetland forest studies.

Mangrove and other tropical wetland forests in a nutshell

Forested wetland ecosystems usually occur in intertidal zones of tropical and subtropical regions of the World (Saenger *et al.* 1983, Tomlinson 1986, Kathiresan & Bingham 2001, Lin & Dushoff 2004, Hogarth 2007, Sharma 2018; [Figure 2A](#)). The most common forest type characterizing these ecosystems is called mangrove or mangal (*sensu* Macnae 1969). Mangroves are typically dominated by a handful of tree species to which the term mangrove is also commonly applied. Mangrove forests are strongly influenced by tidal dynamics and occur in environments with variable salinity, from nearly fresh to hypersaline, with their optimal development in brackish water (Blasco *et al.* 2001, Agráz-Hernández *et al.* 2006). Due to their morphological and physiological attributes, mangrove trees can tolerate high temperatures, salinity, and anaerobiosis in frequently flooded substrates (Tomlinson 1986, Hogarth

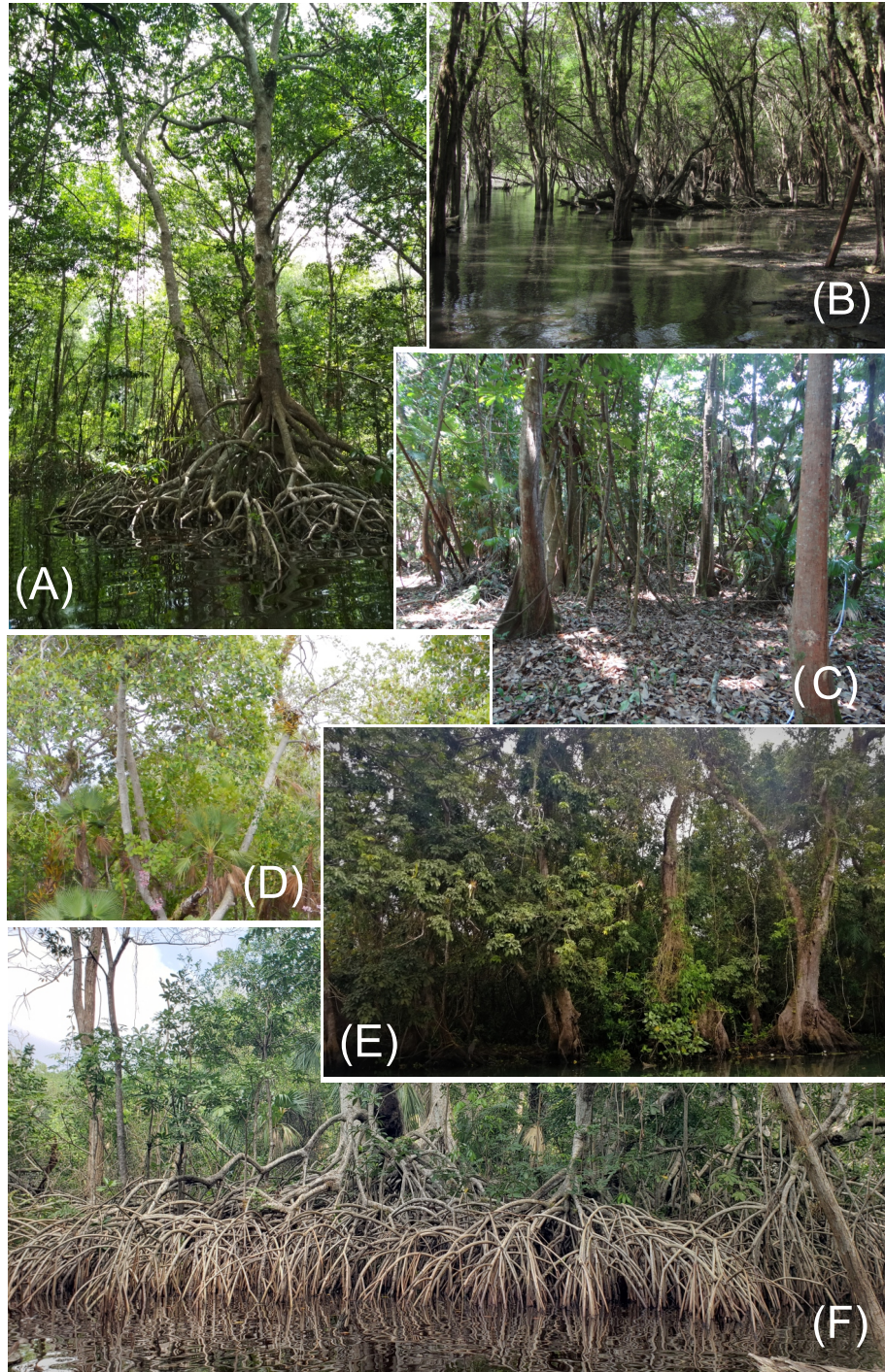


Figure 1. Images of tropical wetland forests in Mexico. Wetland forests encompass mainly mangroves but also other forests which are subjected to permanent or periodic flooding. (A) Mangrove forest dominated by *Rhizophora mangle* L. in Pantanos de Centla Biosphere Reserve, Tabasco. (B) Tintal (seasonally flooded forest dominated by *Haematoxylum campechianum* L.) in Nahá–Metzabok Biosphere Reserve, Chiapas. (C) Pukteal (seasonally flooded forest dominated by *Terminalia buceras* (L.) C. Wright), Pantanos de Centla Biosphere Reserve, Tabasco. (D) Wetland forest with tasiste palm (*Acoelorrhaphe wrightii* (Griseb. & H.Wendl.) H.Wendl. ex Becc.), Pantanos de Centla Biosphere Reserve, Tabasco. (E) Apompal (wetland forest dominated by *Pachira aquatica* Aubl.), Sontecomapan Lagoon, Veracruz. (F) Mangrove forest in El Cometa Lagoon, Tabasco. Photographs: Daniel Chávez (A), Jorge A. Meave (B, D), Derio Jiménez-López (C), Guillermo Ibarra-Manríquez (E), Jorge López-Portillo (F).

2007, Sharma 2018). These attributes include aerial roots that anchor plants in unstable substrates, respiratory roots (pneumatophores and lenticels) to increase access to atmospheric oxygen, regulation of water potential through variation of xylem salt concentration, stomatal regulation, and atmospheric water uptake, and salt secretion through specialized foliar glands (López-Portillo *et al.* 2014, Coopman *et al.* 2021), vivipary (germination on the branches of the parental tree), and hydrochorous dispersal of their propagules (Blasco *et al.* 2001, Kathiresan & Bingham 2001, Zhou *et al.* 2016). Although many of these physiological features also apply to non-mangrove wetland forests, these tend to develop in very low to no salinity conditions; their canopies are composed of a less limited number of tree and palm species, among which members of *Terminalia*, *Acoelorrhaphe* and *Pachira* are frequent (Figure 1C, D, E).

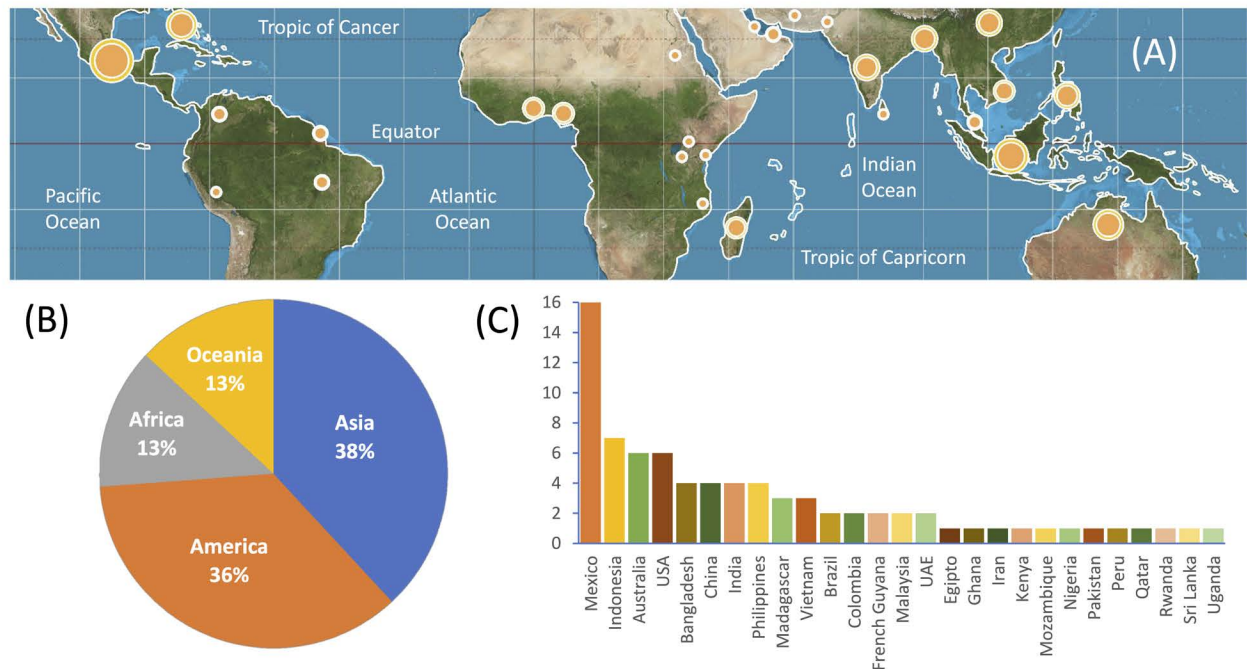


Figure 2. (A) Potential distribution of tropical wetland forests in the tropical regions of the world (30° N to 30° S). The white lines depict the coastlines of all continents where wetland forests may be found; due to scale, inland wetland forests are not shown (modified from Polidoro *et al.* 2010). Note the occurrence of wetland forests in arid regions of the world. The orange circles represent the locations (countries) of remote sensing-based wetland forest studies reviewed in this work; the circle size indicates the number of studies reviewed by country, according to the information shown in panel (C). (B) Continental distribution of the remote sensing-based wetland forest studies included in this review. (C) Distribution of these studies by country; USA, United States of America; UAE, United Arab Emirates. The fact of having recorded more studies from Mexico than from other countries is partly due to the higher ability of the authors to find more studies that were not easily accessible from this country. Map in (A) taken from Wikipedia (Strebe, CC BY-SA 3.0 <<https://creativecommons.org/licenses/by-sa/3.0/>>, via Wikimedia Commons).

A notable feature of wetland forests compared with upland tropical forest types is their low species richness, particularly in the case of mangrove forests. Although species richness varies among biogeographical regions (Tomlinson 1986), the total known species richness for mangrove forests ranges from 55 to 73 taxa (Polidoro *et al.* 2010, Spalding *et al.* 2010), with Avicenniaceae and Rhizophoraceae being the most species-rich and abundant families (Hogarth 2007). Despite the relatively low tree diversity, wetland forests are recognized for their high productivity and the provision of essential ecosystem services (Whittaker & Likens 1973, Odum & Heald 1975, Tomlinson 1986, Kathiresan & Bingham 2001, Sharma 2018), including coastal protection, carbon sequestration, provision of habitat for migratory species, reproductive grounds for a specialized fauna including economically important species for fisheries, and provision of wood (Saenger *et al.* 1983, Lin & Dushoff 2004, Charcape-Ravelo & Moutarde 2005, FAO 2005a, Kuenzer *et al.* 2011).

Despite the unique character of wetland forests, their ecological fragility and high societal value, the present situation for most of them is alarming (Alongi 2008, Islam *et al.* 2014, Himes-Cornell *et al.* 2018). Factors responsible for their deterioration include both human activities (agriculture, cattle ranching, aquaculture, tourism) and natural phenomena, mainly tropical storms and climate change (Charcape-Ravelo & Moutarde 2005, Agráz-Hernández *et al.* 2006, Gilman *et al.* 2008, Kovacs *et al.* 2009, Cho & Qi 2023). These factors have significantly contributed to the loss of their cover worldwide (Polidoro *et al.* 2010), which in mangrove forests alone was between 20 and 35 % in the 1980-2005 period (Kathiresan & Bingham 2001, FAO 2005b, Hogarth 2007, Flores Mejía *et al.* 2010, Giri *et al.* 2011, Barbier *et al.* 2011), and have brought about a growing need to conserve and restore them. In this context, remote sensing is an option with great potential for efficiently studying mangroves and other wetland forests (Mahdavi *et al.* 2018).

Historical overview of remote sensing-based wetland forests studies

Early development of remote sensing took place in a military context (van der Meer *et al.* 2001). Nonetheless, remote sensing found its way since early times in ecosystem studies (Kumar *et al.* 2001). At first, aerial photographs were essential to assess and identify natural resources through forest inventories (West 1956, Colwell 1964, Aschbacher *et al.* 1995, Wang *et al.* 2019). Some inventories included mangrove cover of a region or country in thematic maps (*e.g.*, FAO 1963, Flores Mata *et al.* 1971, Vázquez-Yanes 1971, Blasco *et al.* 1998, Sulong *et al.* 2002, FAO 2005b, Valderrama *et al.* 2014). MacDonald *et al.* (1971) published one of the earliest examples of the use of radar imagery to study coastal landscapes.

With the launching of the first artificial satellites to explore the territory in the 1970s, remote sensing studies underwent explosive diversification, and their coverage expanded to the entire planet (Wulder *et al.* 2019). Interestingly, the first formal publications in remote sensing were seemingly related to the study of wetlands, some of which included mangrove forests (Eitel 1974, Butera 1983, Hardisky *et al.* 1986, Guo *et al.* 2017). To our knowledge, Biña *et al.* (1978) and Lorenzo *et al.* (1979) published the first analyses of spatial changes in mangroves and the monitoring of their deterioration in Southeast Asia based on Landsat images. The use of satellite imagery grew considerably during the following decade; the diversification of platforms (Landsat, SPOT, ERS-1, RADAR) increased the options to study and demarcate wetland forests, particularly mangrove communities (Herz & Jaskow 1985, Dutrieux *et al.* 1990, FAO 2005b, Lucas *et al.* 2007, Kovacs *et al.* 2008, Abdel-Hamid *et al.* 2018, Mahdavi *et al.* 2018). Over time, the remote sensing approach was applied to the study of mangroves in many tropical regions of the world (*e.g.*, Pasqualini *et al.* 1999, Saito *et al.* 2003, Kovacs *et al.* 2005, Satyanarayana *et al.* 2011: [Figure 2B, C](#)), with theoretical and technological tools providing higher-quality information on the status of vegetation at each locality (Zhang *et al.* 2023). More recently, community structural attributes of wetland forests (*e.g.*, aboveground biomass, canopy height) have been explored using mathematical modeling (Couteron *et al.* 2005, Kayitakire *et al.* 2006, Proisy *et al.* 2007), and LiDAR (Light Detection and Ranging; Owers *et al.* 2018, Pereira *et al.* 2018, Koma *et al.* 2021), although wetland forest mapping and monitoring continue to prevail (*e.g.*, Sulong *et al.* 2002, Saito *et al.* 2003, Adam *et al.* 2010, Barbier *et al.* 2011, Alsaaidh *et al.* 2013, Jones *et al.* 2016, Chatziantoniou *et al.* 2017, Guo *et al.* 2017, Yevugah *et al.* 2017, Roy *et al.* 2019, Li *et al.* 2023, Steenvoorden *et al.* 2023; [Figure 3A](#)).

Spatial delimitation and mapping of mangroves and other wetland forests

A fundamental aim in the study of mangroves and other wetland forests through remote sensing has been the definition of their spatial limits (Dale *et al.* 1996, Hirano *et al.* 2003, Yang *et al.* 2009, Margono *et al.* 2014, Wang *et al.* 2019, Steinbach *et al.* 2023), which is the basis for their cartographic expression ([Figure 3A](#)). This is a necessary step to understand the persistence of wetland forests or the changes in their spatial coverage over time (Kovacs *et al.* 2001, Guerra Martínez & Ochoa Gaona 2006, Ren *et al.* 2011, Mansaray *et al.* 2016, Maryantika & Lin 2017, Roy *et al.* 2019, Pan *et al.* 2020, Zhang *et al.* 2023). Aerial photography, Landsat, and SPOT imagery are among the most widely used inputs in the study of wetland forests due to their availability and continuity ([Figure 3B](#); [Tables 1, 2](#)).

Most studies using satellite images are based on the analysis of vegetation reflectance (Fei *et al.* 2011, Kuenzer *et al.* 2011, Abdel-Hamid *et al.* 2018, Apostolopoulos *et al.* 2023) under the tenet of an existing relationship between reflectance values recorded in the image and terrain features (Colwell 1974). However, the rapid development and growth of other remote sensing technologies, in particular LiDAR, have unlocked new ways to explore how the various elements of ecosystem structure impact functional diversity and ecosystem services (Mascaro *et al.* 2011, Asner *et al.* 2012, Davies & Asner 2014, Owers *et al.* 2018). LiDAR is rapidly transitioning from a demonstrative concept to a pivotal tool for estimating carbon stocks in tropical forests (Asner *et al.* 2012) and is thus effective at generating accurate above-ground biomass maps for mangroves, enabling carbon stock assessment and facilitating coastal management (Pereira *et al.* 2018).

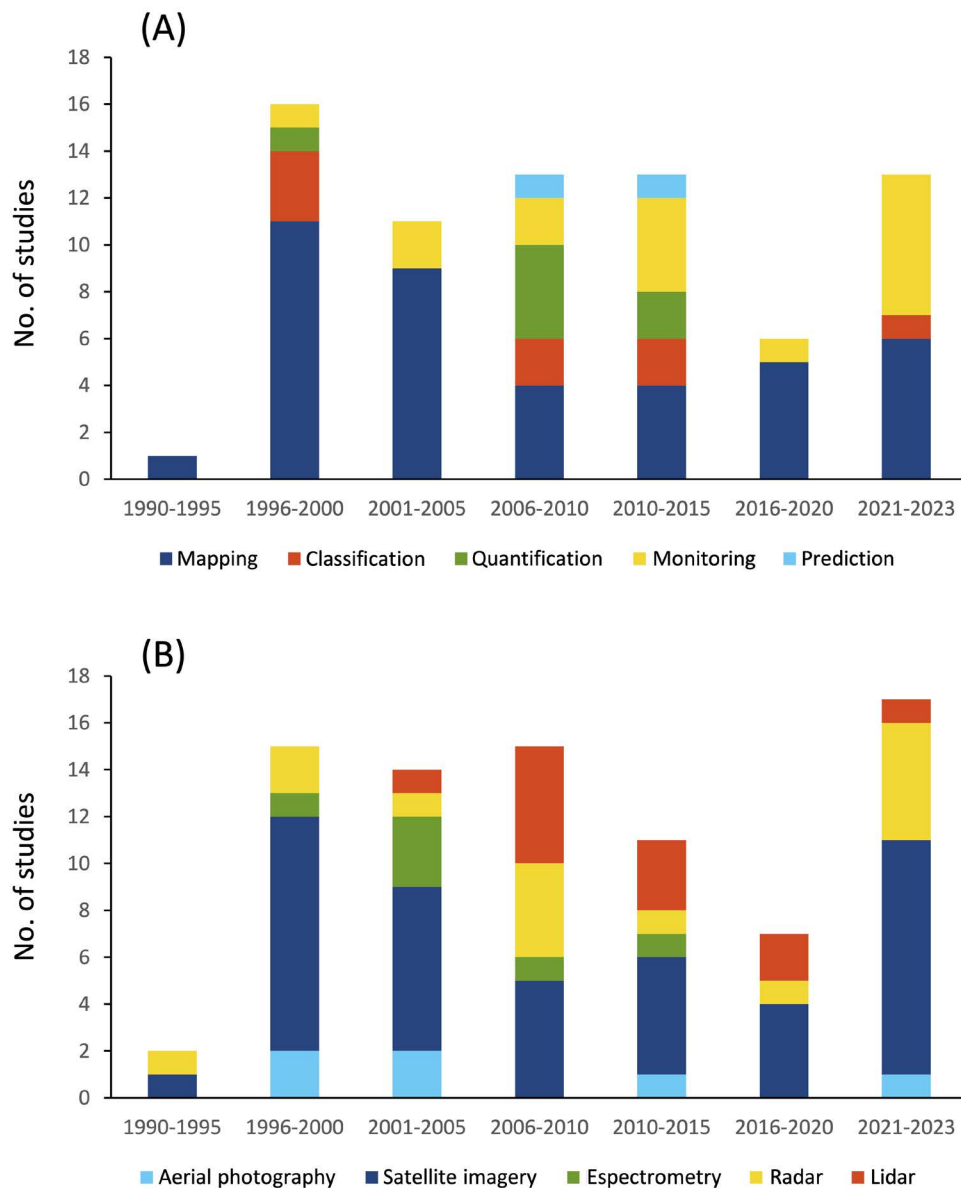


Figure 3. Temporal trends observed in remote sensing-based studies of wetland forests in the 1971-2023 period. (A) Temporal trends in the development of studies according to the main five goals identified in this review. (B) Temporal trend in the remote sensing inputs used by these studies.

Table 1. Classification of remote sensing-based wetland forests studies according to their main goals, resources, and platforms. Explanation of goals: Mapping, spatial delimitation of wetland forests on cartography; Classification, recognition of the different wetland types, including wetland forests, differing in structure, species composition, or health condition; Quantification, assessment of quantitative characteristics of wetland forests, particularly structural attributes; Monitoring, multi-temporal assessment of wetland forests properties to detect trends of change; Prediction, construction of models relating characteristics of the remote sensing resources and vegetation properties to predict forest attributes in sites lacking field data. See [Table 2](#) for explanations of remote sensing input acronyms.

Remote sensing inputs	Mapping	Classification	Quantification	Monitoring	Prediction
<i>Passive sensors</i>					
Aerial photography	8, 20, 63, 85	7		12, 25, 51, 55, 85	
Satellite imagery					
Landsat	10, 15, 18, 19, 23, 48, 54, 58, 61, 70, 77.	11, 47, 73, 86	2, 35, 83	3, 13, 27, 29, 31, 43, 44, 53, 55, 60, 64, 68, 80, 81, 87, 91, 92, 93, 94	82
Sentinel-2	67, 70, 79, 84, 88, 89, 90		72	92	82
SPOT	5, 8, 9, 10, 14, 24, 70	47		4, 6, 12	
IKONOS	26, 28				34, 46
QuickBird	26, 41	38		80	
Google Earth	58, 66				
RapidEye			72		
Hyperion		57		76	
PlanetScope			72		
WorldView	65, 70			51	
Kompsat			75		
ICESAT	37				
Radiometer	24				
Spectrometer					
CASI	10, 21, 45				
AVIRIS	22				
ASD FieldSpec		52			
Field Spec Pro		39			

Using remote sensing to study wetland forests

Remote sensing inputs	Mapping	Classification	Quantification	Monitoring	Prediction
<i>Active sensors</i>					
Radar					
Sentinel-1	84, 88, 90	86			
Polarimetric Radar	1, 5, 16, 17, 71	11, 47		69	
AIRSAR	21				
ENVISAT ASAR	36				
SRTM	30, 37		35	91	
ERS-1 SAR	16			69	
PALSAR	54, 58	50	33	69	
LIDAR	42, 56, 59, 63, 78		49	62, 87	
GLAS	37, 78				

¹MacDonald *et al.* (1971), ²Bina *et al.* (1978), ³Lorenzo *et al.* (1979), ⁴Dutrieux *et al.* (1990), ⁵Aschbacher *et al.* (1995), ⁶Ramsey III & Jensen (1996), ⁷Dale *et al.* (1996); ⁸Blasco *et al.* (1998), ⁹Gao (1998), ¹⁰Green *et al.* (1998b), ¹¹Ramsey III *et al.* (1998), ¹²Rasolofoharinoro *et al.* (1998), ¹⁴Pasqualini *et al.* (1999), ¹⁵Koutsias *et al.* (2000), ¹⁶Kushwaha *et al.* (2000), ¹⁷Proisy *et al.* (2000), ¹⁸Kovacs *et al.* (2001), ¹⁹Foody *et al.* (2001), ²⁰Sulong *et al.* (2002), ²¹Held *et al.* (2003), ²²Hirano *et al.* (2003), ²³Hossain *et al.* (2003), ²⁴Saito *et al.* (2003), ²⁵Dahdouh-Guebas *et al.* (2004), ²⁶Wang *et al.* (2004); ²⁷Hernández Cornejo *et al.* (2005), ²⁸Kovacs *et al.* (2005); ²⁹Berlanga-Robles & Ruiz-Luna (2006), ³⁰Simard *et al.* (2006), ³¹Berlanga-Robles & Ruiz-Luna (2007), ³²Jensen *et al.* (2007), ³³Lucas *et al.* (2007), ³⁴Proisy *et al.* (2007), ³⁵Fatoyinbo *et al.* (2008), ³⁶Kovacs *et al.* (2008), ³⁷Simard *et al.* (2008), ³⁸Myint *et al.* (2011), ³⁹Wang & Sousa (2009), ⁴⁰Yang *et al.* (2009), ⁴¹Kovacs *et al.* (2009), ⁴²Fatoyinbo & Armstrong (2010), ⁴³Berlanga-Robles & Ruiz-Luna (2011), ⁴⁴Giri *et al.* (2011), ⁴⁵Kamal & Phinn (2011), ⁴⁶Satyanarayana *et al.* (2011), ⁴⁷Fei *et al.* (2011), ⁴⁸Alsaaidh *et al.* (2013); ⁴⁹Wannasiri *et al.* (2013); ⁵⁰Darmawan *et al.* (2014); ⁵¹Heenkenda *et al.* (2014); ⁵²Zhang *et al.* (2014); ⁵³Mabwoga Thukral (2014); ⁵⁴Margono *et al.* (2014); ⁵⁵Valderrama *et al.* (2014), ⁵⁶David & Ballardo (2015), ⁵⁷Demuro & Chisholm (2015), ⁵⁸Aslan *et al.* (2016), ⁵⁹David & Ballardo (2016), ⁶⁰Jia *et al.* (2016), ⁶¹Jones *et al.* (2016), ⁶²Pada *et al.* (2016), ⁶³David & Ballardo (2016), ⁶⁴Mansaray *et al.* (2016), ⁶⁵Shahzad *et al.* (2017), ⁶⁶Yevugah *et al.* (2017), ⁶⁷Chatziantoniou *et al.* (2017), ⁶⁸Maryantika & Lin (2017), ⁶⁹Thomas *et al.* (2017), ⁷⁰Valderrama-Landeros *et al.* (2018), ⁷¹Abdel-Hamid *et al.* (2018), ⁷²Baloloy *et al.* (2018), ⁷³Gupta *et al.* (2018), ⁷⁴Islam & Ma (2018), ⁷⁵Solórzano *et al.* (2018), ⁷⁶Pandey *et al.* (2019), ⁷⁷Roy *et al.* (2019), ⁷⁸Hu *et al.* (2020), ⁷⁹Mahdianpari *et al.* (2020), ⁸⁰Pan *et al.* (2020), ⁸¹Mao *et al.* (2021), ⁸²Nguyen & Nguyen (2021), ⁸³Nguyen *et al.* (2021), ⁸⁴De Luca *et al.* (2022), ⁸⁵Apostolopoulos *et al.* (2023), ⁸⁶Cho & Qi (2023), ⁸⁷Flores-de-Santiago *et al.* (2023), ⁸⁸Hemati *et al.* (2023), ⁸⁹Li *et al.* (2023), ⁹⁰Pham *et al.* (2023), ⁹¹Shafi *et al.* (2023), ⁹²Steinbach *et al.* (2023), ⁹³Waleed *et al.* (2023), ⁹⁴Zhang *et al.* (2023).

Efforts to map mangroves and other wetland forests have faced methodological challenges due to their highly variable spectral characteristics and similar reflectance spectra with the underlying soil (Adam *et al.* 2010, Shahzad *et al.* 2017). Early studies pursuing this goal based on Landsat imagery (Biña *et al.* 1978, Lorenzo *et al.* 1979) produced results fraught with significant uncertainty in setting the spatial limits of these communities. This situation improved with the development of new sensors with higher spatial and spectral resolution (Table 3), allowing greater precision to discriminate mangroves from other types of cover (Aschbacher *et al.* 1995, Gao 1998, Blasco *et al.* 1998, Pasqualini *et al.* 1999). At the turn of the century, the availability of very high-resolution imagery (*i.e.*, pixels < 4 m; QuickBird, GeoEye-1, Worldview-2) opened the possibility to map wetland forests areas in greater detail; however, aerial photography is still being used (Sulong *et al.* 2002, Hirano *et al.* 2003, Wang *et al.* 2004, Guo *et al.* 2017), mainly because of their potential to discriminate the different species that occur in these communities (Kamal & Phinn 2011, Valderrama-Landeros *et al.* 2018).

The platforms for acquiring satellite imagery are classified as passive sensors because they use solar radiation to capture terrain details. Other types of sensors are known as active because they emit energy and record its reflection, rendering them independent from physical and weather conditions at image acquisition, such as illumination, cloudiness, and water bodies (Aschbacher *et al.* 1995, Green *et al.* 1998a, China 2002, Kovacs *et al.* 2008, Kuenzer *et al.* 2011, Li *et al.* 2023). Interestingly, recognizing the advantages of contrasting sensor types led to their combined use (Held *et al.* 2003, Asner *et al.* 2008, Simard *et al.* 2008, Aslan *et al.* 2016), increasing the capacity and efficacy to detect, differentiate and estimate wetland forest structure (Ramsey III *et al.* 1998, Rasolofoharino *et al.* 1998, Kayitakire *et al.* 2006, Aslan *et al.* 2016, Wang *et al.* 2019, De Luca *et al.* 2022, Steenvoorden *et al.* 2023). Likewise, precision in mangrove and other wetland forests mapping has improved by combining hyperspectral with multispectral, high, and very high-resolution images (Apostolopoulos *et al.* 2023). This procedure allows the detection of the spectral signature (Shaw & Burke 2003, Navulur 2007, Pandey *et al.* 2019) and a more accurate location of precise wetland forest limits (Blasco *et al.* 1998, Hossain *et al.* 2003, Adam *et al.* 2010).

Monitoring wetland forest dynamics

The possibility of accurately delimiting the territorial extent of wetland forests is also relevant when aiming to assess their losses or gains, as well as their horizontal displacements (Dahdouh-Guebas *et al.* 2004, Hernández Cornejo *et al.* 2005, Shafi *et al.* 2023). In remote sensing, one of the most popular methods for these goals is identifying the presence of a wetland forest through terrain reflectance values (Ingram *et al.* 1981, Ramsey III & Jensen 1996, Mahdavi *et al.* 2018, Wang *et al.* 2019). Although temporal differences in reflectance may represent variations in illumination, atmospheric conditions, and soil moisture, among other factors, there is no doubt that they also reflect changes in vegetation cover (Singh 1989).

Table 2. Explanation of acronyms of remote sensing inputs listed in [Table 1](#) and [Table 3](#).

Acronym	Explanation
SPOT	Satellite Pour l'Observation de la Terre
ICESAT	Ice, Cloud and Land Elevation Satellite
CASI	Compact Airborne Spectrographic Imager
AVIRIS	Airborne visible/infrared imaging spectrometer
AIRSAR	Airborne Synthetic Aperture Radar
ENVISAT ASAR	ENVISAT Advanced Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
ERS-1 SAR	European Remote-Sensing Satellite-1 Synthetic Aperture Radar
PALSAR	Phased Array type L-band Synthetic Aperture Radar
LIDAR	Light Detection and Ranging
GLAS	Geoscience Laser Altimeter System

Interestingly, despite the large availability of satellite-based resources, aerial photography remains essential for monitoring wetland forest dynamics due to an extensive series of aerial photographs of coastal regions predating the satellite-dominated age of remote sensing. The combined use of aerial photographs with satellite images and Geographic Information Systems (GIS) has yielded accurate assessments of wetland areas reductions (Dahdouh-Guebas *et al.* 2004, Heenkenda *et al.* 2014, Apostolopoulos *et al.* 2023). However, when the period delimited for

the analysis of wetland forest dynamics does not include the pre-satellite image era, the studies are based primarily on satellite imagery (Figure 3B). For example, in a multi-temporal analysis of landscape changes associated with coastal wetlands, Berlanga-Robles & Ruiz-Luna (2006, 2007, 2011) successfully assessed losses in wetland cover over a 20-yr period based on the use of the panchromatic bands of Landsat imagery. Using a similar approach, Giri *et al.* (2011) made a more precise assessment of the extent of wetlands worldwide, including both herbaceous and forested wetlands, which was used to update previous reports on these ecosystems by FAO (2005b) and correct previous overestimation. Through the amalgamation of LiDAR and other remote sensing techniques, Asner *et al.* (2008) not only identified and tracked invasive plant species but also evaluated their ecological impact and provided accurate geographical data for conservation and management initiatives. This latter approach holds a huge potential for identifying species in low-diversity ecosystems, such as wetland forests, where the possibility of confounding the radiometric signals from a multitude of species is much more limited than in species-rich upland tropical forests. New and more precise assessments of the extent and limits of wetland forests are needed to provide a more robust basis to evaluate coverage changes, particularly the losses, of these ecosystems worldwide (Shafi *et al.* 2023).

The increasingly accurate assessment of temporal changes in vegetation structure and other aspects of wetland forest communities has benefited from the use of vegetation indices, which consist of numerical relationships between different spectral bands in the images. Among the many existing indices, the most used in wetland forests studies are the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), and the Normalized Difference Water Index (NDWI) (McFeeters 1996, Gao 1998, Kovacs *et al.* 2005, Alsaadeh *et al.* 2013, Kafy *et al.* 2023, Shafi *et al.* 2023). By minimizing the effects of factors linked to biophysical terrain parameters, vegetation indices provide reliable multi-temporal information on the conservation status and the functionality of these systems (Gao 1996, Huete *et al.* 1997, Gao 1998, Saito *et al.* 2003, Wang *et al.* 2004, Nasiri *et al.* 2022, Li *et al.* 2023).

The launching of new technologies has enabled the use of more detailed sources of information (Pada *et al.* 2016, Tassi & Vizzari 2020, Pham *et al.* 2023). Along with the progress in image processing and classification techniques with new analytical algorithms, we have increased our capacity to assess temporal changes in wetland forests accurately (Heenkenda *et al.* 2014, De Luca *et al.* 2022, Pan *et al.* 2022, Shafi *et al.* 2023). Within this framework, one of the most promising developments for mapping and monitoring wetland forests is Google Earth Engine (GEE), a free cloud-based platform to process vast geospatial datasets that allows users to access, observe and analyze geospatial data across the entire planet (Gorelick *et al.* 2017, Tassi & Vizzari 2020, Kafy *et al.* 2023). The GEE platform contains petabytes of fully accessible images from multiple remote sensing platforms; it offers an enormous volume of Earth observation data and high-performance parallel computing equipment to analyze them (Rahaman & Shermin 2022, Hemati *et al.* 2023). Thus, one major advantage of operating on the GEE platform is a significant reduction in satellite image processing time, which in a short period has contributed to improving the assessment of land use and land cover change, on top of traditional mapping and vegetation monitoring efforts (Mahdianpari *et al.* 2020, Nasiri *et al.* 2022). In addition, the integration of machine learning algorithms into the GEE platform has considerably accelerated the gathering of valuable information about the state of wetland forests, and thus are handy new tools for the classification, mapping, and monitoring of these ecosystems compared to traditional methods (Tassi & Vizzari 2020, Waleed *et al.* 2023, Flores-de Santiago *et al.* 2023).

Modeling and predicting wetland forest community attributes through remote sensing

In the advancement of remote sensing, particularly concerning the study of vegetation, one of the most prominent developments refers to the use of the characteristics of digital images to model community diversity and structural attributes (*e.g.*, basal area, biomass, crown cover, stem density, species richness, canopy height) with various degrees of precision and certitude (Strahler *et al.* 1986, Woodcock & Strahler 1987, China 2002, Chuvieco 2020). The basic tenet of vegetation attribute modeling from images acquired through remote sensors establishes the possibility of constructing algorithms relating image spectral features (*i.e.*, reflectance) with the physical attributes of the terrain (*e.g.*, Strahler *et al.* 1986, Woodcock & Strahler 1987, Nagendra & Rocchini 2008).

Table 3. Synthesis of the temporal, spatial and radiometric resolutions of the different remote sensing platforms used for the study of tropical wetland forests. Please note that for Landsat, Sentinel and Spot, the information for all the sensors used in their different missions is condensed and the resolutions are given as ranges. NA, not applicable.

Platform	Number of bands	Temporal resolution (days)	Spatial resolution (m)	Radiometric resolution (μm)*
Aerial photography	NA	Variable (on demand)	1	NA
Landsat	2 to 9	16 to 18	15 to 100	0.475 to 12.51
Sentinel-2	12	6 to 10	5 to 60	0.43 to 2.28
SPOT	4 to 5	26	1.5 to 20	0.45 to 1.75
IKONOS	4	14	1 to 4	0.45 to 0.90
QuickBird	5	2.8	0.65 to 2.4	0.45 to 0.90
RapidEye	5	1	5	0.4 to 0.85
Hyperion	220	1 to 2	10 to 30	0.4 to 2.5
PlanetScope	8	1	3	0.43 to 0.88
WorldView	9	1.1	0.5 to 2.0	0.45 to 0.9
Kompsat-2	4	28	1 to 4	0.45 to 0.9
ICESAT	NA	91	NA	0.532
CASI	228	85 frames/sec	1	1.9
AVIRIS	224	Variable (on demand)	20	0.4 to 2.5
FieldSpec Pro	2,151	Variable (on demand)	30	0.35 to 2.5
Polarimetric Radar	NA	NA	3 to 30	9.47 GHz
SAR	NA	NA	5	20 to 80 MHz
GLAS	NA	91	NA	0.532

* Except in the case of Polarimetric Radar and SAR, whose resolution is GHz and MHz, respectively.

Despite substantial progress made with this approach in the last decade, modeling and predicting wetland forest attributes remain a relatively little explored field of research (Proisy *et al.* 2007, Giri 2016). As early attempts in this direction, Lucas *et al.* (2007) and Simard *et al.* (2006) produced examples of mangrove attribute estimations based on remote sensing data acquired through active sensors: Advanced Land Observing Satellite/L-band polarimetric SAR (ALOS-PALSAR) and Ice, Cloud, and Land Elevation Satellite/Geoscience Laser Altimeter System (ICESat/GLAS). This early work delivered the foundations for a study that, to this date, continues to stand out as the most successful effort in the realm of wetland forest attribute modeling. This is the work of Proisy *et al.* (2007), who predicted biomass in mangrove forests of French Guyana. Their work relied on two novel theoretical and methodological contributions in modern remote sensing: the concept of image surface metrics and the FOTO (Fourier-based Textural Ordination) method to predict mangrove biomass based on very high-resolution (1 m) IKONOS imagery (Table 3).

Surface metrics quantify pixel spatial distribution and reflectance in an image and are closely related to landscape heterogeneity (McGarigal *et al.* 2009). Every pixel in a scene contains reflectance data for various wavelengths with valuable information on the structural composition of the surfaces (Haralik *et al.* 1973, Strahler *et al.* 1986, Woodcock & Strahler 1987, Shaw & Burke 2003). There are two types of surface metrics: (1) first-order or tonal metrics, calculated from the analysis of the reflectance recorded in individual pixels, and (2) second-order surface metrics,

also known as textural metrics, calculated with the spectral values of at least two (but usually more) contiguous pixels (Haralik 1979).

Proisy *et al.* (2007)'s study represents the first successful attempt to predict mangrove biomass using high-resolution satellite imagery. From their work, relevant conclusions emerged, for example, regarding the optimal pixel window size for biomass modeling. For this reason, this work is an essential reference to study mangrove forests from a perspective based on the analysis of the spatial relationships of the components both in the images and on the terrain. The findings of this study triggered much research in many temperate (Block *et al.* 2016) and tropical (Couteron *et al.* 2005, Ploton *et al.* 2012, Solórzano *et al.* 2017) plant communities, including successional forests (Gallardo-Cruz *et al.* 2012). However, its impact on wetland forest studies is relatively modest. A notable exception is a study conducted by Solórzano *et al.* (2018), also based on high-resolution imagery and in the contrast of FOTO and GLCM (Gray Level Co-occurrence Matrix), two commonly used methods to analyze image texture. Despite the clear advantages of using these methodological tools for the accurate prediction of wetland forest attributes, recent studies continue to use tonal metrics and multiple regression as the basis for the prediction of forest attributes such as aboveground biomass and carbon stocks (Baloloy *et al.* 2018, Hu *et al.* 2020, Nguyen & Nguyen 2021). Therefore, the two approaches will likely continue to co-exist for some time.

Future challenges in the study of wetland forests through remote sensing

Notwithstanding the key conceptual and methodological developments achieved in the field of remote sensing focused on the study of mangroves and other wetland forests, the best-known aspect of these communities across the tropics continues to be their spatial distribution (Table 1). Indeed, wetland forests delimitation and mapping continue to be essential tasks that will allow us to evaluate as precisely as possible its territorial extent, loss, or expansion (Green *et al.* 1998b, Blasco *et al.* 1998, Sulong *et al.* 2002, Wang *et al.* 2019, Nguyen *et al.* 2021). Nonetheless, it is also true that remote sensing approaches have opened many possibilities of analysis previously unforeseen, and many of them are only now beginning to be fully appreciated.

Research on wetland forests through remote sensing has faced challenges that have sometimes caused biases in the type of studies conducted, mainly favoring the mapping of these ecosystems, leaving the quantification and modeling of their structural attributes on a second plane. The main challenge is the modeling of some wetland forests characteristics, such as the complex salinity-flooding relationship (Thom 1967, Semeniuk 1980, Tomlinson 1986), that distinguish them from terrestrial ecosystems (Chatziantoniou *et al.* 2017), along with the difficulty to discriminate wetland forests, particularly mangroves, from other adjacent forest types using satellite imagery and other remote sensing inputs (Gupta *et al.* 2018). Due to the complex and highly dynamic flooding regimes that characterize wetland forests, acquiring the reflectance information of the site from remote sensing inputs is challenging. This difficulty points to the need for new methodological approaches. A promising alternative is to combine active and passive sensors as an efficient way to provide a more accurate depiction of the physical characteristics of these communities (Aschbacher *et al.* 1995, Green *et al.* 1998a, Kushwaha *et al.* 2000, Fatoyinbo *et al.* 2008, Kovacs *et al.* 2008, Aslan *et al.* 2016), even though to this date these studies continue to rely more heavily on passive than on active sensors (Figure 3B). Additional alternatives for the study of wetland forests imply working at different scales because different sensors are likely to capture different aspects of their variation (Steenvoorden *et al.* 2023). Finally, it would be valuable to use existing indices or propose new and more exact methods to extract specific biophysical parameters (Wannasiri *et al.* 2013), such as reducing the exposed water surfaces for more accurate estimates of community attributes.

While numerous LiDAR-based studies have utilized aerial vehicles for terrain data acquisition, there has been a recent emergence of the use of Terrestrial Laser Scanning (TLS), involving sensors positioned on the ground (Fröhlich & Mettenleiter 2004, Liang *et al.* 2016). Recent studies have showcased the effectiveness of TLS technology in precisely quantifying biomass within intricate coastal wetland vegetation. For example, Owers *et al.* (2018) demonstrated a good match between TLS-derived estimates of mangrove biomass and conventional allometric tech-

niques. Furthermore, the dependability of TLS is reinforced by 3D surface reconstruction models, resulting in comparable above-ground biomass estimates for mangroves.

The concept of nature-based coastal protection is gaining increasing traction as a promising, sustainable, and cost-effective strategy to mitigate the risks of coastal flooding (van Hespén *et al.* 2023). Wetland forests, with their remarkable wave-attenuating capabilities, play a significant role in this natural approach to flood defense. Moreover, the restoration of mangroves and other wetland forests not only enhances flood resilience but also catalyzes substantial economic growth (Debrot *et al.* 2022).

Wetlands play a pivotal role in disaster prevention, water quality improvement, and carbon storage. Given that remote sensing technology can guide restoration efforts, as well as surveillance and monitoring, especially through high-resolution platforms, such as IKONOS, Hyperion, QuickBird and PlanetScope (Table 3), we urge governments and international organizations to make greater investments in remote sensing-based research and to use it as a law enforcement tool for the protection of these threatened ecosystems.

Final remarks

The world of remote sensing is constantly growing. With the rapid development of remote sensing imagery, new approaches have emerged; undoubtedly, there are still some unresolved difficulties (Nasiri *et al.* 2022, Pan *et al.* 2022). Remote sensing-based studies of mangrove and other wetland forest communities have accomplished half a century of development. Despite such a long period of constant advancement, it is noteworthy that most studies in this field have focused on the delimitation and mapping of this ecosystem. Notably, current remote sensing studies of wetland forests also address new research questions with novel goals and aims. A limited but rapidly growing number of studies have aimed at modeling and predicting various wetland forest attributes, especially their biomass and three-dimensional structure. However, this type of research still represents a small fraction of all remote sensing-based studies focused on these ecosystems. The difficulty to accurately describe and predict community attributes in forests that possess such a complex physical structure will likely be overcome by using LiDAR and radar-based techniques (Darmawan *et al.* 2014, David & Ballardo 2015, 2016) and by increasing the use of machine learning and other automated information analysis processes (Mahdianpari *et al.* 2020, Yang *et al.* 2022, Pham *et al.* 2023).

Considering the critical conservation issues of wetland ecosystems (Kathiresan & Bingham 2001, Lee *et al.* 2014, Islam *et al.* 2014) in the face of global warming (Soares 2009, Sandilyan & Kathiresan 2012), the need to gather accurate and reliable information on these systems has become a matter of urgency. Modeling wetland forest attributes from remote sensing inputs promises to achieve this goal. However, the study of wetland forests through remote sensing is still in an early stage of development. In the future, we will undoubtedly witness conceptual and methodological progress that will enable us to surmount the challenges remaining to this date.

Acknowledgments

We are grateful to Marco Antonio Romero Romero and Abril Chávez for figure preparation. This paper is in partial fulfillment of the Programa de Doctorado en Ciencias Biológicas, Universidad Nacional Autónoma de México. The authors have no conflict of interest to declare.

Literature cited

- Abdel-Hamid A, Dubovyk O, El-Magd IA, Menz G. 2018. Mapping mangroves extents on the Red Sea coastline in Egypt using polarimetric SAR and high resolution optical remote sensing data. *Sustainability* 10: 646. DOI: <https://doi.org/10.3390/su10030646>
- Adam E, Mutanga O, Rugege D. 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. *Wetlands Ecology and Management* 18: 281-296. DOI: <https://doi.org/10.1007/s11273-009-9169-z>

- Agráz-Hernández C, Noriega-Trejo R, López-Portillo J, Flores-Verdugo JF, Jiménez-Zacarias J. 2006. *Guía de Campo. Identificación de los Manglares en México*. Campeche: Universidad Autónoma de Campeche. ISBN: 968 5722-45-5
- Al-Naimi N, Al-Ghouti MA, Balakrishnan P. 2016 Investigating chlorophyll and nitrogen levels of mangroves at Al-Khor, Qatar: an integrated chemical analysis and remote sensing approach. *Environmental Monitoring and Assessment* 188: 268. DOI: <https://doi.org/10.1007/s10661-016-5269-4>
- Alongi DM. 2008. Mangrove forests: resilience, protection from tsunamis, and responses to global climate change. *Estuarine, Coastal and Shelf Science* 76: 1-13. DOI: <https://doi.org/10.1016/j.ecss.2007.08.024>
- Alsaaidh B, Al-Hanbali A, Tateishi R, Kobayashi T, Hoan NT. 2013. Mangrove forests mapping in the southern part of Japan using Landsat ETM+ with DEM. *Journal of Geographic Information System* 5: 369-377. DOI: <http://doi.org/10.4236/jgis.2013.54035>
- Aplin P. 2004. Remote sensing: land cover. *Progress in Physical Geography* 28: 283-293. DOI: <https://doi.org/10.1191/0309133304pp413pr>
- Apostolopoulos DN, Giannikopoulos D, Ramfos A, Faulwetter S, Panagiotaras D, Nikolakopoulos KG, Avramidis P. 2023. Monitoring Kotychi Lagoon in western Peloponnese, Greece, using remote sensing techniques and environmental assessment. *Journal of Marine Science and Engineering* 11: 411. DOI: <https://doi.org/10.3390/jmse11020411>
- Aschbacher J, Ofren R, Delsol JP, Suselo TB, Vibulsresth S, Charrupat T. 1995. An integrated comparative approach to mangrove vegetation mapping using advanced remote sensing and GIS technologies: preliminary results. *Hydrobiologia* 295: 285-294. DOI: <https://doi.org/10.1007/BF00029135>
- Aslan A, Rahman AF, Warren MW, Robeson SM. 2016. Mapping spatial distribution and biomass of coastal wetland vegetation in Indonesian Papua by combining active and passive remotely sensed data. *Remote Sensing of Environment* 183: 65-81. DOI: <https://doi.org/10.1016/j.rse.2016.04.026>
- Asner GP, Hughes RF, Vitousek PM, Knapp DE, Kennedy-Bowdoin T, Boardman J, Martin RE, Eastwood M, Green RO. 2008. Invasive plants transform the three-dimensional structure of rain forests. *Proceedings of the National Academy of Sciences of the United States of America* 105: 4519-4523. DOI: <https://doi.org/10.1073/pnas.0710811105>
- Asner GP, Mascaro J, Muller-Landau HC, Vieilledent G, Vaudry R, Rasamoelina M, Hall JS, van Breugel M. 2012. A universal airborne LiDAR approach for tropical forest carbon mapping. *Oecologia* 168: 1147-1160. DOI: <https://doi.org/10.1007/s00442-011-2165-z>
- Baloloy AB, Blanco AC, Candido CG, Argamosa RJL, Dumlalag JBL, Dimapilis LLC, Paringit EC. 2018. Estimation of mangrove forest above ground biomass using multispectral bands, vegetation indices and biophysical variables derived from optical satellite imageries: RapidEye, PlanetScope and Sentinel-2. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 4: 29-36. DOI: <https://doi.org/10.5194/isprs-annals-IV-3-29-2018>
- Barbier EB, Hacker SD, Kennedy C, Koch EW, Stier AC, Silliman BR. 2011. The value of estuarine and coastal ecosystems services. *Ecological Monographs* 81: 169-193. DOI: <https://doi.org/10.1890/10-1510.1>
- Berlanga-Robles CA, Ruiz-Luna A. 2006. Evaluación de cambios en el paisaje y sus efectos sobre los humedales costeros del sistema estuarino de San Blas, Nayarit (México) por medio de análisis de imágenes Landsat. *Ciencias Marinas* 32: 523-538.
- Berlanga-Robles CA, Ruiz-Luna A. 2007. Análisis de las tendencias de cambio del bosque de mangle del sistema lagunar Teacapán-Agua Brava, México. Una aproximación con el uso de imágenes de satélite Landsat. *Universidad y Ciencia* 23: 29-46.
- Berlanga-Robles CA, Ruiz-Luna A. 2011. Integrating remote sensing techniques, Geographical Information Systems (GIS), and stochastic models for monitoring Land Use and Land Cover (LULC) changes in the Northern Coastal Region of Nayarit, Mexico. *GIScience Remote Sensing* 48: 245-263. DOI: <https://doi.org/10.2747/1548-1603.48.2.245>

- Biña RT, Jara RS, De Jesus BR, Lorenzo EN. 1978. Mangrove inventory of the Philippines using LANDSAT multi-spectral data and the IMAGE 100 system. *NRMC Research Monograph* 2: 1-8.
- Blasco F, Carayon JL, Aizpuru M. 2001. World mangrove resources. *ISME/GLOMIS Electronic Journal* 1: 1-3.
- Blasco F, Gauquelin T, Rasolofoharinoro M, Denis J, Aizpuru M, Caldirou V. 1998. Recent advances in mangrove studies using remote sensing data. *Marine and Freshwater Research* 49: 287-296. DOI: <https://doi.org/10.1071/MF97153>
- Block S, González EJ, Gallardo-Cruz JA, Fernández A, Solórzano JV, Meave JA. 2016. Using Google Earth surface metrics to predict plant species richness in a complex landscape. *Remote Sensing* 8: 865. DOI: <https://doi.org/10.3390/rs8100865>
- Butera MK. 1983. Remote sensing of wetlands. *IEEE Transactions on Geoscience and Remote Sensing* 21: 383-392. DOI: <https://doi.org/10.1109/TGRS.1983.350471>
- Charcape-Ravelo M, Moutarde F. 2005. Diversidad florística y conservación del Santuario Regional de Piura Manglares San Pedro de Vice-Sechura. *Revista Peruana de Biología* 12: 327-334.
- Chatziantoniou A, Psomiadis E, Petropoulos GP. 2017. Co-orbital Sentinel 1 and 2 for LULC mapping with emphasis on wetlands in a Mediterranean setting based on machine learning. *Remote Sensing* 9: 1259. DOI: <https://doi.org/10.3390/rs9121259>
- China JD. 2002. Teledetección de bosques tropicales. In: Guariguata MR, Kattan GH, eds. *Ecología de Bosques Neotropicales*. Cartago: Editorial Tecnológica. ISBN: 978-9968801119
- Cho MS, Qi J. 2023. Characterization of the impacts of hydro-dams on wetland inundations in Southeast Asia. *Science of The Total Environment* 864: 160941. DOI: <https://doi.org/10.1016/j.scitotenv.2022.160941>
- Chuvieco E. 2020. *Fundamentals of Satellite Remote Sensing: An Environmental Approach*. Boca Raton: CRC Press. ISBN: 978-1138583832
- Colwell JE. 1974. Vegetation canopy reflectance. *Remote Sensing of Environment* 3: 175-183. DOI: [https://doi.org/10.1016/0034-4257\(74\)90003-0](https://doi.org/10.1016/0034-4257(74)90003-0)
- Colwell RN. 1964. Aerial photography - a valuable sensor for the scientist. *American Scientist* 52: 17-49.
- Coopman RE, Nguyen HT, Mencuccini M, Oliveira RS, Sack L, Lovelock CE, Ball MC. 2021. Harvesting water from unsaturated atmospheres: deliquescence of salt secreted onto leaf surfaces drives reverse sap flow in a dominant arid climate mangrove, *Avicennia marina*. *New Phytologist* 231: 1401-1414. DOI: <https://doi.org/10.1111/nph.17461>
- Couteron P, Pelissier R, Nicolini EA, Paget D. 2005. Predicting tropical forests stand structure parameters from Fourier transform of very high-resolution remotely sensed canopy images. *Journal of Applied Ecology* 42: 1121-1128. DOI: <https://doi.org/10.1111/j.1365-2664.2005.01097.x>
- Dahdouh-Guebas F, Van Pottelbergh I, Kairo JG, Cannicci S, Koedam N. 2004. Human-impacted mangroves in Gazi (Kenya): predicting future vegetation based on retrospective remote sensing, social surveys, and tree distribution. *Marine Ecology Progress Series* 272: 77-92. DOI: <https://doi.org/10.3354/meps272077>
- Dale PER, Chandica AL, Evans M. 1996. Using image subtraction and classification to evaluate change in sub-tropical intertidal wetlands. *International Journal of Remote Sensing* 17: 703-719. DOI: <https://doi.org/10.1080/01431169608949039>
- Darmawan S, Takeuchi W, Vetrina Y, Winarso G, Wikantika K, Sari DK. 2014. Characterization of mangrove forest types based on ALOS-PALSAR in overall Indonesian archipelago. *IOP Conference Series: Earth and Environmental Science* 20: 1-8. DOI: <https://doi.org/10.1088/1755-1315/20/1/012051>
- David LCG, Ballardo AH. 2015 Mapping mangrove forest from LiDAR data using object-based image analysis and support vector machine: the case of Calatagan, Batangas. 2015 *International Conference on Humanoid Nanotechnology Information Technology Communication and Control Environment and Management, (HNICEM)*, pp. 1-5. DOI: <https://doi.org/10.1109/HNICEM.2015.7393167>
- David LCG, Ballardo AH. 2016 Object-based use and land cover mapping from LiDAR data and orthophoto application of decision tree-based data selection for SVM classification. 2016 *IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, 2016, pp. 1-5. DOI: <https://doi.org/10.1109/R10-HTC.2016.7906854>

- Davies AB, Asner GP. 2014. Advances in animal ecology from 3D-LiDAR ecosystem mapping. *Trends in Ecology & Evolution* 29: 681-691. DOI: <https://doi.org/10.1016/j.tree.2014.10.005>
- De Luca G, Silva JMN, Di Fazio S, Modica G. 2022. Integrated use of Sentinel-1 and Sentinel-2 data and open-source Machine Learning algorithms for land cover mapping in a Mediterranean region. *European Journal of Remote Sensing* 55: 52-72. DOI: <https://doi.org/10.1080/22797254.2021.2018667>
- Debrot AO, Plas A, Boesono H, Prihantoko K, Baptist MJ, Mur, AJ, Tonneijck FH. 2022. Early increases in artisanal shore-based fisheries in a Nature-based Solutions mangrove rehabilitation Project on the north coast of Java. *Estuarine, Coastal and Shelf Science* 267: 107761. DOI: <https://doi.org/10.1016/j.ecss.2022.107761>
- Demuro M, Chisholm L. 2015 Assessment of Hyperion for characterizing mangrove communities. In: *Proceedings of the 12th JPLAVIRIS Airborne Earth Science Workshop*, pp. 18-23. Pasadena.
- Dutrieux E, Denis J, Populus J. 1990. Application of SPOT data to a base-line ecological study of the Mahakam delta mangroves (East Kalimantan, Indonesia). *Oceanologica Acta* 13: 317-326.
- Eitel DF. 1974. An overview of remote sensing for wetlands investigations. In: Shahrokhi F, ed. *Remote Sensing of Earth Resources, Vol. 1*. Nashville: University of Tennessee. pp. 179-192.
- Einzmann K, Atzberger C, Pinnel N, Glas C, Böck S, Seitz R, Immitzer M. 2021. Early detection of spruce vitality loss with hyperspectral data: results of an experimental study in Bavaria, Germany. *Remote Sensing of Environment* 266: 112676. DOI: <https://doi.org/10.1016/j.rse.2021.112676>
- FAO [Food and Agriculture Organization of the United Nations]. 1963. *World Forest Inventory 1963*. Rome: FAO.
- FAO [Food and Agriculture Organization of the United Nations]. 2005a. *Evaluación de los recursos forestales mundiales 2005: Estudio temático sobre manglares*. México Perfil Nacional. Rome: FAO.
- FAO [Food and Agriculture Organization of the United Nations]. 2005b. *The World's Mangroves 1980-2005: A Thematic Study Prepared in the Framework of the Global Forest Resources Assessment 2005*. Rome: FAO.
- Fatoyinbo TE, Armstrong AH. 2010. Remote characterization of biomass measurements: case study of mangrove forest. In: Momba M, Bux F, eds. *Biomass*. Rijeka: InTech. ISBN: 978-953-307-1138
- Fatoyinbo TE, Simard M, Washington-Allen RA, Shugart HH. 2008. Landscape-scale extent, height, biomass, and carbon estimation of Mozambique's mangrove forests with Landsat ETM+ and Shuttle Radar Topography Mission elevation data. *Journal of Geophysical Research* 113: G02S06. DOI: <https://doi.org/10.1029/2007JG000551>
- Fei SX, Shan CH, Hua GZ. 2011. Remote sensing of mangrove wetlands identification. *Procedia Environmental Sciences* 10: 2287-2293. DOI: <https://doi.org/10.1016/j.proenv.2011.09.357>
- Flores-de Santiago F, Rodríguez-Sobreyra R, Álvarez-Sánchez LF, Valderrama-Landeros L, Amezcua F, Flores-Verdugo F. 2023. Understanding the natural expansion of white mangrove (*Laguncularia racemosa*) in an ephemeral inlet based on geomorphological analysis and remote sensing data. *Journal of Environmental Management* 338: 117820. DOI: <https://doi.org/10.1016/j.jenvman.2023.117820>
- Flores Mata G, Jiménez López J, Madrigal Sánchez X, Moncayo Ruiz F, Takaki Takaki F. 1971. Memoria del Mapa de Tipos de Vegetación de la República Mexicana. Mexico City: Dirección de Agrología, Secretaría de Recursos Hidráulicos.
- Flores Mejía MA, Aguirre Vallejo A, Flores Hernández M, Guardado Govea X. 2010. El impacto que produce el sector turismo en los manglares de las costas mexicanas. *ContactoS* 77: 33-38.
- Foody GM. 2003. Remote sensing of tropical forest environments: towards the monitoring of environmental resources for sustainable development. *International Journal of Remote Sensing* 24: 4035-4046. DOI: <https://doi.org/10.1080/0143116031000103853>
- Foody GM, Cutler ME, McMorrow J, Pelz D, Tangki H, Boyd DS, Douglas I. 2001. Mapping the biomass of Bornean tropical rain forest from remotely sensed data. *Global Ecology and Biogeography* 10: 379-387. DOI: <https://doi.org/10.1046/j.1466-822X.2001.00248.x>
- Fröhlich C, Mettenleiter M. 2004. Terrestrial laser scanning-new perspectives in 3D surveying. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 36: W2.

- Gallardo-Cruz JA, Meave JA, González EJ, Lebrija-Trejos E, Romero-Romero MA, Pérez-García EA, Gallardo-Cruz R, Hernández-Stefanoni JL, Martorell C. 2012. Predicting tropical dry forest successional attributes from space: is the key hidden in image texture? *Plos One* 7: e30506. DOI: <https://doi.org/10.1371/journal.pone.0030506>
- Gao B. 1996. NDWI - A Normalized Difference Water Index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58: 257-266. DOI: [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3)
- Gao J. 1998. A hybrid method toward accurate mapping of mangroves in a marginal habitat from SPOT multispectral data. *Journal of Remote Sensing* 19: 1887-1899. DOI: <https://doi.org/10.1080/014311698215045>
- Gilman EL, Ellison J, Duke NC, Field C. 2008. Threats to mangroves from climate change and adaptation options: a review. *Aquatic Botany* 89: 237-250. DOI: <https://doi.org/10.1016/j.aquabot.2007.12.009>
- Giri C. 2016. Observation and monitoring of mangrove forests using remote sensing: Opportunities and challenges. *Remote Sensing* 8: 783. DOI: <https://doi.org/10.3390/rs8090783>
- Giri C, Ochieng E, Tieszen LL, Zhu Z, Singh A, Loveland T, Masek J, Duke N. 2011. Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography* 20: 154-159. DOI: <https://doi.org/10.1111/j.1466-8238.2010.00584.x>
- Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing Environmental* 202: 18-27. DOI: <https://doi.org/10.1016/j.rse.2017.06.031>
- Green EP, Clark CD, Mumby PJ, Edwards AJ, Ellis AC. 1998a. Remote sensing techniques for mangrove mapping. *International Journal of Remote Sensing* 19: 935-956. DOI: <https://doi.org/10.1080/014311698215801>
- Green EP, Mumby PJ, Clark CD, Ellis AC. 1998b. The assessment of mangrove areas using high resolution multi-spectral airborne imagery. *Journal of Coastal Research* 14: 433-443.
- Guerra Martínez V, Ochoa Gaona S. 2006. Forest and land use assessment from 1990 to the year 2000 in Pantanos de Centla Biosphere Reserve, Tabasco, Mexico. *Investigaciones Geográficas* 59: 7-25.
- Guo M, Li J, Shen C, Xu J, Wu L. 2017. A review of wetland remote sensing. *Sensors* 17: 777. DOI: <https://doi.org/10.3390/s17040777>
- Gupta K, Mukhopadhyay A, Giri S, Chanda A, Datta Majumdar S, Samanta S, Mitra D, Samal RN, Pattnaik AK, Hazra S. 2018. An index for discrimination of mangroves from non-mangroves using LANDSAT 8 OLI imagery. *MethodsX* 5: 1129-1139. DOI: <https://doi.org/10.1016/j.mex.2018.09.011>
- Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR, Kommareddy A, Egorov A, Chini L, Justice CO, Townshend JRG. 2013. High-resolution global maps of 21st-century forest cover change. *Science* 342: 850-853. DOI: <https://doi.org/10.1126/science.1244693>
- Haralik RM. 1979. Statistical and structural approaches to texture. *Proceedings of the Institute of Electrical and Electronics Engineers* 67: 786-804. DOI: <https://doi.org/10.1109/PROC.1979.11328>
- Haralik RM, Shanmugam K, Dinstein I. 1973. Textural features for image classification. *Proceedings of the Institute of Electrical and Electronics Engineers Transactions on Systems, Man, and Cybernetics* 3: 610-621. DOI: <https://doi.org/10.1109/TSMC.1973.4309314>
- Hardisky MA, Gross MF, Klemas V. 1986. Remote sensing of coastal wetlands. *Bioscience* 36: 453-459. DOI: <https://doi.org/10.2307/1310341>
- Heenkenda MK, Joyce KE, Maier SW, Bartolo R. 2014. Mangrove species identification: comparing WorldView-2 with aerial photographs. *Remote Sensing* 6: 6064-6088. DOI: <https://doi.org/10.3390/rs6076064>
- Held A, Ticehurst C, Lymburner L, Williams N. 2003. High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing* 24: 2739-2759. DOI: <https://doi.org/10.1080/0143116031000066323>
- Hemati MA, Hasanlou M, Mahdianpari M, Mohammadimanesh F. 2023. Iranian wetland inventory map at a spatial resolution of 10 m using Sentinel-1 and Sentinel-2 data on the Google Earth Engine cloud computing platform. *Environmental Monitoring and Assessment* 195: 558. DOI: <https://doi.org/10.1007/s10661-023-11202-z>

- Hernández Cornejo R, Koedam N, Ruiz Luna A, Troell M, Dahdouh-Guebas F. 2005. Remote sensing and ethnobotanical assessment of the mangrove forest changes in the Navachiste-San Ignacio-Macapule Lagoon complex, Sinaloa, Mexico. *Ecology and Society* 10: 16. DOI: <https://doi.org/10.5751/ES-01286-100116>
- Herz R, Jaskow A. 1985. Remote sensing of mangrove areas on the Brazilian coast. *Proceedings of the Coastal Zone 85*, Baltimore, Maryland, USA. ISBN: 978-0872624733
- Himes-Cornell A, Pendleton L, Atiyah P. 2018. Valuing ecosystem services from blue forests: a systematic review of the valuation of salt marshes, sea grass beds and mangrove forests. *Ecosystem Services* 30: 36-48. DOI: <https://doi.org/10.1016/j.ecoser.2018.01.006>
- Hirano A, Madden M, Welch R. 2003. Hyperspectral image data for mapping wetland vegetation. *Wetlands* 23: 436-448. DOI: <https://doi.org/10.1672/18-20>
- Hogarth P. 2007. *The Biology of Mangroves and Seagrasses*. New York: Oxford University Press. DOI: <https://doi.org/10.1093/acprof:oso/9780198568704.001.0001>
- Hossain MS, Lin K, Hussain MZ. 2003. Remote sensing and GIS applications for suitable mangrove afforestation area selection in the coastal zone of Bangladesh. *Geocarto International* 18: 61-65. DOI: <https://doi.org/10.1080/10106040308542264>
- Hu T, Zhang YY, Su Y, Zheng Y, Lin G, Guo Q. 2020. Mapping the global mangrove forest aboveground biomass using multisource remote sensing data. *Remote Sensing* 12: 1690. DOI: <https://doi.org/10.3390/rs12101690>
- Huete AR. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25: 295-309. DOI: [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Huete AR, Liu HQ, van Leeuwen WJD. 1997. The use of vegetation indices in forested regions: issues of linearity and saturation. In: IGARSS'97. 1997 Proceedings. IEEE International Geoscience and Remote Sensing Symposium Remote Sensing-A Scientific Vision for Sustainable Development, Vol. 4, pp. 1966-1968. DOI: <https://doi.org/10.1109/IGARSS.1997.609169>
- Infante Mata D, Moreno-Casasola P, Madero-Vega C, Castillo-Campos G, Warner BG. 2011. Floristic composition and soil characteristics of tropical freshwater forested wetlands on the coastal plain of the Gulf of Mexico. *Forest Ecology and Management* 262: 1514-1531. DOI: <https://doi.org/10.1016/j.foreco.2011.06.053>
- Ingram K, Knap E, Robinson JW. 1981. *Change detection technique development for improved urbanized area delineation, technical memorandum CSCITM-81/6087*. Maryland: Computer Sciences Corporation.
- Islam SN. 2010. Threatened wetlands and ecologically sensitive ecosystems management in Bangladesh. *Frontiers of Earth Science in China* 4: 438-448. DOI: <https://doi.org/10.1007/s11707-010-0127-0>
- Islam SN, Gnauck A, Voigt HJ, Eslamian S. 2014. Hydrological changes in mangrove ecosystems. In: Eslamian S, ed. *Handbook of Engineering Hydrology*. Boca Raton: CRC Press, pp. 369-390. DOI: <https://doi.org/10.1201/b16683-22>
- Islam S, Ma M. 2018. Geospatial monitoring of land surface temperature effects on vegetation dynamics in the southeastern region of Bangladesh from 2001 to 2016. *ISPRS International Journal of Geo-Information* 7: 486. DOI: <https://doi.org/10.3390/ijgi7120486>
- Jensen R, Mausel P, Dias N, Gonser R, Yang C, Everitt J, Fletcher R. 2007. Spectral analysis of coastal vegetation and land cover using AISA+ hyperspectral data. *Geocarto International* 22: 17-28. DOI: <https://doi.org/10.1080/10106040701204354>
- Jia M, Liu M, Wang Z, Mao D, Ren C, Cui H. 2016. Evaluating the effectiveness of conservation on mangroves: a remote sensing-based comparison for two adjacent protected areas in Shenzhen and Hong Kong, China. *Remote Sensing* 8: 627. DOI: <https://doi.org/10.3390/rs8080627>
- Jones TG, Glass L, Gandhi S, Ravaoarinosihoaana L, Carro A, Benson L, Ratsimba HR, Giri C, Randriamanantena D, Cripps G. 2016. Madagascar's mangroves: quantifying Nation-wide and ecosystem specific dynamics, and detailed contemporary mapping of distinct ecosystems. *Remote Sensing* 8: 106. DOI: <https://doi.org/10.3390/rs8020106>
- Kafy A-A, Saha M, Fattah MA, Rahman MT, Duti BM, Rahaman MT, Bakshi A, Kalaivani S, Rahaman SN, Sattar

- GS. 2023. Integrating forest cover change and carbon storage dynamics: leveraging Google Earth Engine and InVEST model to inform conservation in hilly regions. *Ecological Indicators* 152: 110374. DOI: <https://doi.org/10.1016/j.ecolind.2023.110374>
- Kamal M, Phinn S. 2011. Hyperspectral data for mangrove species mapping: a comparison of pixel-based and object-based approach. *Remote Sensing* 3: 2222-2242. DOI: <https://doi.org/10.3390/rs3102222>
- Kathiresan K, Bingham BL. 2001. Biology of mangroves and mangrove ecosystems. *Advances in Marine Biology* 40: 81-251. DOI: [http://doi.org/10.1016/S0065-2881\(01\)40003-4](http://doi.org/10.1016/S0065-2881(01)40003-4)
- Kayitakire F, Hamel C, Defourny P. 2006. Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. *Remote Sensing of Environment* 102: 390-401. DOI: <https://doi.org/10.1016/j.rse.2006.02.022>
- Koma Z, Zlinszky A, Bekő L, Burai P, Seijmonsbergen AC, Kissling WD. 2021. Quantifying 3D vegetation structure in wetlands using differently measured airborne laser scanning data. *Ecological Indicators* 127: 107752. DOI: <https://doi.org/10.1016/j.ecolind.2021.107752>
- Koutsias N, Karteris M, Chuvieco E. 2000. The use of intensity-hue-saturation transformation of Landsat-5 Thematic Mapper data for burned land mapping. *Photogrammetric Engineering Remote Sensing* 66: 829-239.
- Kovacs JM, Wang J, Blanco-Correa M. 2001. Mapping disturbances in a mangrove forest using multi-date Landsat TM imagery. *Environmental Management* 27: 763-776. DOI: <https://doi.org/10.1007/s002670010186>
- Kovacs JM, Wang J, Flores-Verdugo F. 2005. Mapping mangrove leaf area index at the species level using IKONOS and LAI-2000 sensors for the Agua Brava Lagoon, Mexican Pacific. *Estuarine, Coastal and Shelf Science* 62: 377-384. DOI: <https://doi.org/10.1016/j.ecss.2004.09.027>
- Kovacs JM, Zhang C, Flores-Verdugo FJ. 2008. Mapping the condition of mangroves of the Mexican Pacific using C-band ENVISAT ASAR and Landsat optical data. *Ciencias Marinas* 34: 407-418. DOI: <https://doi.org/10.7773/cm.v34i4.1320>
- Kovacs JM, King JML, Flores de Santiago F, Flores-Verdugo F. 2009. Evaluating the condition of a mangrove forest of the Mexican Pacific based on an estimated leaf area index mapping approach. *Environmental Monitoring and Assessment* 157: 137-149. DOI: <https://doi.org/10.1007/s10661-008-0523-z>
- Kuenzer C, Bluemel A, Gebhardt S, Vo Quoc T, Dech S. 2011. Remote sensing of mangrove ecosystems: a review. *Remote Sensing* 3: 878-928. DOI: <https://doi.org/10.3390/rs3050878>
- Kumar L, Schmidt K, Dury S, Skidmore A. 2001. Imaging spectrometry and vegetation science. In: van der Meer F, de Jong S, eds. *Imaging Spectrometry: Basic Principles and Prospective Applications*. Dordrecht: Springer, pp. 111-155. DOI: https://doi.org/10.1007/978-0-306-47578-8_5
- Kushwaha SPS, Dwivedi RS, Rao BRM. 2000. Evaluation of various digital image processing techniques for detection of coastal wetlands using ERS-1 SAR data. *International Journal of Remote Sensing* 21: 565-579. DOI: <https://doi.org/10.1080/014311600210759>
- Landgrave R, Moreno-Casasola P. 2012. Evaluación cuantitativa de la pérdida de humedales en México. *Investigación Ambiental* 4: 19-35.
- Lee SY, Primavera JH, Dahdouh-Guebas F, McKee K, Bosire JO, Cannicci S, Diele K, Fromard F, Koedam N, Marchand C, Mendelssohn I, Mukherjee N, Record S. 2014. Ecological role and services of tropical mangrove ecosystems: a reassessment. *Global Ecology and Biogeography* 23: 726-743. DOI: <https://doi.org/10.1111/geb.12155>
- Li Y, Bai J, Chen S, Chen B, Zhang L. 2023. Mapping seagrasses on the basis of Sentinel-2 images under tidal change. *Marine Environmental Research* 185: 105880. DOI: <https://doi.org/10.1016/j.marenvres.2023.105880>
- Liang X, Kankare V, Hyypä J, Wang Y, Kukko A, Haggren H, Yu X, Kaartinen H, Jaakkola A, Guan F, Holopainen M, Vastaranta M. 2016. Terrestrial laser scanning in forest inventories. *ISPRS Journal of Photogrammetry and Remote Sensing* 115: 63-77. DOI: <https://doi.org/10.1016/j.isprsjprs.2016.01.006>
- Lin BB, Dushoff J. 2004. Mangrove filtration of anthropogenic nutrients in the Rio Coco Solo, Panama. *Management Quality: An International Journal* 15: 131-142. DOI: <https://doi.org/10.1108/14777830410523071>
- López-Portillo J, Ezcurra E. 2002. Los manglares de México: una revisión. *Madera y Bosques* 8: 27-51. DOI: <https://doi.org/10.21829/myb.2002.801290>

- López-Portillo J, Ewers FW, Méndez-Alonzo R, Paredes López CL, Angeles G, Alarcón Jiménez AL, Lara Domínguez AL, Torres Barrera MC. 2014. Dynamic control of osmolality and ionic composition of the xylem sap in two mangrove species. *American Journal of Botany* 101: 1013-1022. DOI: <https://doi.org/10.3732/ajb.1300435>
- Lorenzo EN, de Jesús Jr BR, Jara RS. 1979. Assessment of mangrove forest deterioration in Zamboanga Peninsula, Philippines using Landsat MSS data, *Proceedings of the Thirteenth International Symposium on Remote Sensing of Environment* 25-27 April, Michigan, Ann Arbor, Michigan: Environmental Research Institute of Michigan.
- Lu D, Mausel P, Brondizio E, Moran E. 2004. Relationships between forest stand parameters and Landsat TM spectral responses in the Brazilian Amazon Basin. *Forest Ecology and Management* 198: 149-167. DOI: <https://doi.org/10.1016/j.foreco.2004.03.048>
- Lucas RM, Mitchell AL, Rosenqvist A, Proisy C, Melius A, Ticehurst C. 2007. The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the Tropics. *Aquatic Conservation: Marine and Freshwater Ecosystems* 17: 245-264. DOI: <https://doi.org/10.1002/aqc.833>
- Mabwoga SO, Thukral AK. 2014. Characterization of change in the Harike wetland, a Ramsar site in India, using Landsat satellite data. *SpringerPlus* 3: 576. DOI: <https://doi.org/10.1186/2193-1801-3-576>
- MacDonald HC, Lewis AJ, Wing RS. 1971. Mapping and landform analysis of coastal regions with radar. *GSA Bulletin* 82: 345-358. DOI: [https://doi.org/10.1130/0016-7606\(1971\)82%5b345:MALOCR%5d2.0.CO;2](https://doi.org/10.1130/0016-7606(1971)82%5b345:MALOCR%5d2.0.CO;2)
- Macnae W. 1969. A general account of the fauna and flora of mangrove swamps and forests in the Indo-West Pacific region. *Advances in Marine Biology* 6: 73-103, 104a, 104b, 105-270. DOI: [https://doi.org/10.1016/S0065-2881\(08\)60438-1](https://doi.org/10.1016/S0065-2881(08)60438-1)
- Mahdavi S, Salehi B, Granger J, Amani M, Brisco B, Huang W. 2018. Remote sensing for wetland classification: a comprehensive review. *GIScience & Remote Sensing* 55: 623-658. DOI: <https://doi.org/10.1080/15481603.2017.1419602>
- Mahdianpari M, Salehi B, Mohammadimanesh F, Brisco B, homayouni S, Gill E, DeLancey ER, Bourgeau-Chavez L. 2020. Big data for a big country: The first generation of Canadian wetland inventory map at a Spatial Resolution of 10-m using Sentinel-1 and Sentinel-2 data on the Google Earth Engine cloud computing platform. *Canadian Journal of Remote Sensing* 46: 15-33. DOI: <https://doi.org/10.1080/07038992.2019.1711366>
- Mansaray LR, Huang J, Kamara AA. 2016. Mapping deforestation and urban expansion in Freetown, Sierra Leone, from pre- to post-war economic recovery. *Environmental Monitoring and Assessment* 188: 470. DOI: <https://doi.org/10.1007/s10661-016-5469-y>
- Mao D, Tian Y, Wang Z, Jia M, Du J, Song C. 2021. Wetland changes in the Amur River Basin: differing trends and proximate causes on the Chinese and Russian sides. *Journal of Environmental Management* 280: 111670. DOI: <https://doi.org/10.1016/j.jenvman.2020.111670>
- Margono BA, Bwangoy J-RB, Potapov PV, Hansen MC. 2014. Mapping wetlands in Indonesia using Landsat and PALSAR data-sets and derived topographical indices. *Geo-spatial Information Science* 17: 60-71. DOI: <https://doi.org/10.1080/10095020.2014.898560>
- Maryantika N, Lin C. 2017. Exploring changes of land use and mangrove distribution in the economic area of Sidoarjo District, East Java using multi-temporal Landsat images. *Information Processing in Agriculture* 4: 321-332. DOI: <https://doi.org/10.1016/j.inpa.2017.06.003>
- Mascaro J, Detto M, Asner GP, Muller-Landau HC. 2011. Evaluating uncertainty in mapping forest carbon with airborne LiDAR. *Remote Sensing of Environment* 115: 3770-3774. DOI: <https://doi.org/10.1016/j.rse.2011.07.019>
- McFeeters SK. 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing* 17: 1425-1432. DOI: <https://doi.org/10.1080/01431169608948714>
- McGarigal K, Tagil S, Cushman SA. 2009. Surface metrics: an alternative to patch metrics for the quantification of landscape structure. *Landscape Ecology* 24: 433-450. DOI: <https://doi.org/10.1007/s10980-009-9327-y>
- Mezaal MR, Pradhan B, Shafri HZM, Yusoff ZM. 2017. Automatic landslide detection using Dempster-Shafter theory from LiDAR-derived data and orthophotos. *Geomatics, Natural Hazards and Risk* 8: 1935-1954. DOI: <https://doi.org/10.1080/19475705.2017.1401013>

- Moreno-Casasola P, López Rosas H, Infante Mata D, Peralta LA, Travieso-Bello AC, Warner BG. 2009. Environmental and anthropogenic factors associated with coastal wetland differentiation in La Mancha, Veracruz, Mexico. *Plant Ecology* 200: 37-52. DOI: <https://doi.org/10.1007/s11258-008-9400-7>
- Myint SW, Gober P, Brazel A, Grossman-Clarke S, Weng Q. 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sensing of Environment* 115: 1145-1161. DOI: <https://doi.org/10.1016/j.rse.2010.12.017>
- Nagendra H, Rocchini D. 2008. High resolution satellite imagery for tropical biodiversity studies: the devil is in the detail. *Biodiversity and Conservation* 17: 3431-3442. DOI: <https://doi.org/10.1007/s10531-008-9479-0>
- Nasiri V, Deljouei A, Moradi F, Sadeghi SMM, Borz SA. 2022. Land Use and Land Cover mapping using Sentinel-2, Landsat-8 satellite images, and Google Earth Engine: a comparison of two composition methods. *Remote Sensing* 14: 1977. DOI: <https://doi.org/10.3390/rs14091977>
- Navulur K. 2007. *Multispectral Image Analysis Using the Object-Oriented Paradigm*. Boca Raton: CRC Press. DOI: <https://doi.org/10.1201/9781420043075>
- Nguyen H-H, Nguyen TTH. 2021. Above-ground biomass estimation models of mangrove forests based on remote sensing and field-surveyed data: implications for C-PFES implementation in Quang Ninh Province, Vietnam. *Regional Studies in Marine Science* 48: 101985. DOI: <https://doi.org/10.1016/j.rsma.2021.101985>
- Nguyen H-H, Vu HD, Röder A. 2021. Estimation of above-ground mangrove biomass using Landsat-8 data-derived vegetation indices: a case study in Quang Ninh Province, Vietnam. *Forest and Society* 5: 506-525. DOI: <https://doi.org/10.24259/fs.v5i2.13755>
- Odum WE, Heald EJ. 1975. The detritus-based food web of an estuarine mangrove community. In: Cronin LE, ed. *International Estuarine Research Conference*. New York: Academic Press, pp. 265-286. ISBN: 9780323142700
- Owers CJ, Rogers K, Woodroffe CD. 2018. Terrestrial laser scanning to quantify above-ground biomass of structurally complex coastal wetland vegetation. *Estuarine, Coastal and Shelf Science* 204: 164-176. DOI: <https://doi.org/10.1016/j.ecss.2018.02.027>
- Pada AV, Silapan J, Cabanlit MA, Campomanes F, Garcia JJ. 2016. Mangrove forest cover extraction of the coastal areas of Negros Occidental, Western Visayas, Philippines using LiDAR data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLI-B1. DOI: <https://doi.org/10.5194/isprs-archives-XLI-B1-73-2016>
- Pan W-H, Chen J-J, Wang Y. 2020. Analysis of spatio-temporal dynamical change and landscape characteristics of mangroves and *Spartina alterniflora* in Fujian based on satellite imageries from 1999 to 2018. *Journal of Ecology and Rural Environment* 36: 1428-1436. DOI: <https://doi.org/10.19741/j.issn.1673-4831.2020.0487>
- Pan X, Wang Z, Gao Y, Dang X, Han Y. 2022. Detailed an automated classification of land use/land cover using machine learning algorithms in Google Earth Engine. *Geocarto International* 37: 5415-5432. DOI: <https://doi.org/10.1080/10106049.2021.1917005>
- Pandey PC, Anand A, Srivastava PK. 2019. Spatial distribution of mangrove forest species and biomass assessment using field inventory and earth observation hyperspectral data. *Biodiversity and Conservation* 28: 2143-2162. DOI: <https://doi.org/10.1007/s10531-019-01698-8>
- Pasqualini V, Iltis J, Dessay N, Lointier M, Guelorget O, Polidori L. 1999. Mangrove mapping in North-Western Madagascar using SPOT-XS and SIR-C radar data. *Hydrobiologia* 413: 127-133. DOI: <https://doi.org/10.1023/A:1003807330375>
- Pereira FRS, Kampel M, Soares MLG, Estrada GCD, Bentz C, Vincent G. 2018. Reducing uncertainty in mapping of mangrove aboveground biomass using airborne discrete LiDAR data. *Remote Sensing* 10: 637. DOI: <https://doi.org/10.3390/rs10040637>
- Pham H-T, Nguyen H-Q, Le K-P, Tran T-P, Ha N-T. 2023. Automated mapping of wetland ecosystems: a study using Google Earth Engine and machine learning for lotus mapping in Central Vietnam. *Water* 15: 854. DOI: <https://doi.org/10.3390/w15050854>
- Ploton P, Pélissier R, Proisy C, Flavenot T, Barbier N, Rai SN, Coueron P. 2012. Assessing aboveground tropi-

- cal forest biomass using Google Earth canopy images. *Ecological Applications* 22: 993-1003. DOI: <https://doi.org/10.1890/11-1606.1>
- Polidoro BA, Carpenter KE, Collins L, Duke NC, Ellison AM, Ellison JC, Farnsworth EJ, Fernando ES, Kathiresan K, Koedam NE, Livingstone SR, Miyagi T, Moore GE, Nam VN, Ong JE, Primavera JH, Salmo III SG, Sanchiangco JC, Sukardjo S, Wang Y, Yong JWH. 2010. The loss of species: mangrove extinction risk and geographic areas of global concern. *Plos One* 5: e10095. DOI: <https://doi.org/10.1371/journal.pone.0010095>
- Proisy C, Coueron P, Fromard F. 2007. Predicting and mapping mangrove biomass from canopy grain analysis using Fourier-based Textural Ordination of IKONOS images. *Remote Sensing of Environment* 109: 379-392. DOI: <https://doi.org/10.1016/j.rse.2007.01.009>
- Proisy C, Mougin E, Fromard F, Karam MA. 2000. Interpretation of polarimetric Radar signatures of mangrove forests. *Remote Sensing of Environment* 71: 56-66. DOI: [https://doi.org/10.1016/S0034-4257\(99\)00064-4](https://doi.org/10.1016/S0034-4257(99)00064-4)
- Putut Ash Shidiq I, Wibowo A, Kusratmoko E, Indratmoko S, Ardianto R, Prasetyo Nugroho B. 2017. Urban forest topographical mapping using UAV LIDAR. *IOP Conference Series: Earth and Environmental Science* 98: 012034. DOI: <https://doi.org/10.1088/1755-1315/98/1/012034>
- Rahaman SN, Shermin N. 2022. Identifying the effect of monsoon floods on vegetation and land surface temperature by using Google Earth Engine. *Urban Climate* 43: 101162. DOI: <https://doi.org/10.1016/j.uclim.2022.101162>
- Ramsey III EW, Jensen JR. 1996. Remote sensing of mangrove wetlands: relating canopy spectra to site-specific data. *Photogrammetric Engineering Remote Sensing* 62: 939-948.
- Ramsey III EW, Nelson GA, Sapkota SK. 1998. Classifying coastal resources by integrating optical and radar imagery and color infrared photography. *Mangroves and Salt Marshes* 2: 109-119. DOI: <https://doi.org/10.1023/A:1009911224982>
- Rasolofoharinoro M, Blasco F, Bellan MF, Aizpuru M, Gauquelin T, Denis J. 1998. A remote sensing-based methodology for mangrove studies in Madagascar. *International Journal of Remote Sensing* 19: 1873-1886. DOI: <https://doi.org/10.1080/014311698215036>
- Ren H, Wu X, Ning T, Huang G, Wang J, Jian S, Lu H. 2011. Wetland changes and mangrove restoration planning in Shenzhen Bay, Southern China. *Landscape and Ecological Engineering* 7: 241-250. DOI: <https://doi.org/10.1007/s11355-010-0126-z>
- Roy S, Mahapatra M, Chakraborty A. 2019. Mapping and monitoring of mangrove along the Odisha coast based on remote sensing and GIS techniques. *Modeling Earth Systems and Environment* 5: 217-226. DOI: <https://doi.org/10.1007/s40808-018-0529-7>
- Saenger P, Hegerl EJ, Davie JD. 1983. Global status of mangrove ecosystems. *The Environmentalist* 3: 7-79.
- Saito H, Bellan MF, Al-Habshi A, Aizpuru M, Blasco F. 2003. Mangrove research and coastal ecosystem studies with SPOT-4 HRVIR and TERRA ASTER in the Arabian Gulf. *International Journal of Remote Sensing* 24: 4073-4092. DOI: <https://doi.org/10.1080/0143116021000035030>
- Sandilyan S, Kathiresan K. 2012. Mangrove conservation: a global perspective. *Biodiversity and Conservation* 21: 3523-3542. DOI: <https://doi.org/10.1007/s10531-012-0388-x>
- Satyanarayana B, Koedam N, De Smet K, Di Nitto D, Bauwens M, Jayatissa LP, Cannicci S, Dahdouh-Guebas F. 2011. Long-term mangrove forests development in Sri Lanka: early predictions evaluated against outcomes using VHR remote sensing and VHR ground-truth data. *Marine Ecology Progress Series* 443: 51-63. DOI: <https://doi.org/10.3354/meps09397>
- Schowengerdt RA. 2007. *Remote Sensing. Models and Methods for Image Processing*. Burlington: Academic Press. ISBN: 9780080480589
- Semeniuk V. 1980. Mangrove zonation along an eroding coastline in King Sound, North-Western Australia. *Journal of Ecology* 68: 789-812. DOI: <https://doi.org/10.2307/2259456>
- Seppelt R, Dormann CF, Eppink FV, Lautenbach S, Schmidt S. 2011. A quantitative review of ecosystem service studies: approaches, shortcomings and the road ahead. *Journal of Applied Ecology* 48: 630-636. DOI: <https://doi.org/10.1111/j.1365-2664.2010.01952.x>

- Shafi A, Chen S, Waleed M, Sajjad M. 2023. Leveraging machine learning and remote sensing to monitor long-term spatial-temporal wetland changes: Towards a national RAMSAR inventory in Pakistan. *Applied Geography* 151: 102868. DOI: <https://doi.org/10.1016/j.apgeog.2022.102868>
- Shahzad N, Ahmad SR, Ashraf S. 2017. An assessment of pan-sharpening algorithms for mapping mangrove ecosystems: a hybrid approach. *International Journal of Remote Sensing* 38: 1579-1599. DOI: <https://doi.org/10.1080/01431161.2016.1278311>
- Sharma S. 2018. Introductory Chapter: Mangrove ecosystem research trends - where has the focus been so far. In: Sharma S, ed. *Mangrove Ecosystem Ecology and Function*. London: IntechOpen, . 3-13. DOI: <https://doi.org/10.5772/intechopen.80962>
- Shaw G, Burke HK. 2003. Spectral imaging for remote sensing. *Lincoln Laboratory Journal* 14: 3-28.
- Simard M, Rivera-Monroy VH, Mancera-Pineda JE, Castañeda-Moya E, Twilley RR. 2008. A systematic method for 3D mapping of mangrove forests based on Shuttle Radar Topography Mission elevation data, ICESat/GLAS waveforms and field data: application to Ciénaga Grande de Santa Marta, Colombia. *Remote Sensing of Environment* 112: 2131-2144. DOI: <https://doi.org/10.1016/j.rse.2007.10.012>
- Simard M, Zhang K, Rivera-Monroy VH, Ross, MS, Ruiz PL, Castañeda-Moya E, Twilley RR, Rodriguez E. 2006. Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric Engineering and Remote Sensing* 72: 299-311. DOI: <https://doi.org/10.14358/PERS.72.3.299>
- Singh A. 1989. Review article digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing* 10: 989-1003. DOI: <https://doi.org/10.1080/01431168908903939>
- Soares MLG. 2009. A conceptual model for the responses of mangrove forests to sea level rise. *Journal of Coastal Research* 56: 267-271. <https://www.jstor.org/stable/25737579>
- Solórzano JV, Gallardo-Cruz JA, González EJ, Peralta-Carreta C, Hernández-Gómez M, Fernández-Montes de Oca A, Cervantes-Jiménez LG. 2018. Contrasting the potential of Fourier transformed ordination and gray level co-occurrence matrix textures to model a tropical swamp forest's structural and diversity attributes. *Journal of Applied Remote Sensing* 12: 036006. DOI: <https://doi.org/10.1117/1.JRS.12.036006>
- Solórzano JV, Meave JA, Gallardo-Cruz JA, González EJ, Hernández-Stefanoni JL. 2017. Predicting old-growth tropical forest attributes from very high resolution (VHR)-derived surface metrics. *International Journal of Remote Sensing* 38: 492-513. DOI: <https://doi.org/10.1080/01431161.2016.1266108>
- Song L, Liu S, Kustas WP, Zhou J, Xu Z, Xia T, Li M. 2016. Application of remote sensing-based two-source energy balance model for mapping field surface fluxes with composite and component surface temperatures. *Agricultural and Forest Meteorology* 230-231: 8-19. DOI: <https://doi.org/10.1016/j.agrformet.2016.01.005>
- Spalding M, Kainuma M, Collins L. 2010. *World Atlas of Mangroves*. London: ITTO, ISME, FAO, UNEP-WCMC, UNESCO-MAB and UNU-INWEH. Earthscan Publishers Ltd. DOI: <https://doi.org/10.4324/9781849776608>
- Steenvoorden J, Bartholomeus H, Limpens J. 2023. Less is more: Optimizing vegetation mapping in peatlands using unmanned aerial vehicles (UAVs). *International Journal of Applied Earth Observation and Geoinformation* 117: 103220. DOI: <https://doi.org/10.1016/j.jag.2023.103220>
- Steinbach S, Hentschel E, Hentze K, Rienow A, Umulisa V, Zwart SJ, Nelson A. 2023. Automatization and evaluation of a remote sensing-based indicator for wetland health assessment in East Africa on national and local scales. *Ecological Informatics* 75: 102032. DOI: <https://doi.org/10.1016/j.ecoinf.2023.102032>
- Strahler AH, Woodcock CE, Smith JA. 1986. On the nature of models in remote sensing. *Remote Sensing of Environment* 20: 121-139. DOI: [https://doi.org/10.1016/0034-4257\(86\)90018-0](https://doi.org/10.1016/0034-4257(86)90018-0)
- Sulong I, Mohd-Lokman H, Mohd-Tarmizi K, Ismail A. 2002. Mangrove mapping using Landsat imagery and aerial photographs: Kemaman District, Terengganu, Malaysia. *Environment, Development and Sustainability* 4: 135-152. DOI: <https://doi.org/10.1023/A:1020844620215>
- Tassi A, Vizzari M. 2020. Object-oriented LULC classification in Google Earth Engine Combining SNIC, GLCM, and Machine Learning Algorithms. *Remote Sensing* 12: 3776. DOI: <https://doi.org/10.3390/rs12223776>
- Tomlinson PB. 1986. *The Botany of Mangroves*. Cambridge: Cambridge University Press. ISBN: 0-521-25567-8

- Thom BG. 1967 Mangrove ecology and deltaic geomorphology: Tabasco, Mexico. *Journal of Ecology* 55: 301-343. DOI: <https://doi.org/10.2307/2257879>
- Thomas N, Lucas R, Bunting P, Hardy A, Rosenqvist A, Simard M. 2017. Distribution and drivers of global mangrove forest change, 1996-2010. *Plos One* 12: e0179302. DOI: <https://doi.org/10.1371/journal.pone.0179302>
- Turner W, Spector S, Gardiner N, Fladeland M, Sterling E, Steininger M. 2003. Remote sensing for biodiversity science and conservation. *Trends in Ecology and Evolution* 18: 306-314. DOI: [https://doi.org/10.1016/S0169-5347\(03\)00070-3](https://doi.org/10.1016/S0169-5347(03)00070-3)
- Valderrama L, Troche C, Rodríguez MT, Márquez D, Vázquez B, Velázquez S, Vázquez A, Cruz MI, Ressler R. 2014. Evaluation of mangrove cover changes in Mexico during the 1970 – 2005 period. *Wetlands* 34: 747-758. DOI: <https://doi.org/10.1007/s13157-014-0539-9>
- Valderrama-Landeros L, Flores-de-Santiago F, Kovacs JM, Flores-Verdugo F. 2018. An assessment of commonly employed satellite-based remote sensors for mapping mangrove species in Mexico using an NDVI-based classification scheme. *Environmental Monitoring and Assessment* 190: 23. DOI: <https://doi.org/10.1007/s10661-017-6399-z>
- Valiela I, Bowen JL, York JK. 2001. Mangrove forests: one of the world's threatened major tropical environments. *BioScience* 51: 807-815. DOI: [https://doi.org/10.1641/0006-3568\(2001\)051\[0807:MFOOTW\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2001)051[0807:MFOOTW]2.0.CO;2)
- Valtonen A, Korkiatupa E, Holm S, Malinga GM, Nakadai R. 2021. Remotely sensed vegetation greening along a restoration gradient of a tropical forest, Kibale National Park, Uganda. *Land Degradation Development* 32: 5166-5177. DOI: <https://doi.org/10.1002/ldr.4096>
- van der Meer F, De Jong S, Bakker W. 2001. Imaging spectrometry: basic analytical techniques. In: van der Meer F, de Jong S, eds. *Imaging Spectrometry: Basic Principles and Prospective Applications*. Dordrecht: Springer, pp. 17-61. DOI: https://doi.org/10.1007/978-0-306-47578-8_2
- van Hespen R, Hu Z, Borsje B, De Dominicis M, Friess DA, Jevrejeva S, Kleinhans MG, Maza M, van Bijsterveldt CEJ, Van der Stocken T, van Wesenbeeck B, Xie D, Bouma TJ. 2023. Mangrove forest as a nature-based solution for coastal flood protection: biophysical and ecological considerations. *Water Science and Engineering* 16: 1-13. DOI: <https://doi.org/10.1016/j.wse.2022.10.004>
- Viani RAG, Holl KD, Padovezi A, Strassburg BBN, Farah FT, Garcia LC, Chaves RB, Rodrigues RR, Brancalion PHS. 2017. Protocol for monitoring tropical forest restoration: perspectives from the Atlantic forest restoration pact in Brazil. *Tropical Conservation Science* 10: 1-8. DOI: <https://doi.org/10.1177/1940082917697265>
- Vázquez-Yanes C. 1971. La vegetación de la Laguna de Mandinga, Veracruz. *Anales del Instituto de Biología, Universidad Nacional Autónoma de México* 42: 49-94.
- Waleed M, Sajjad M, Shazil MS, Tariq M, Alam MT. 2023. Machine learning-based spatial-temporal assessment and change transition analysis of wetlands: an application of Google Earth Engine in Sylhet, Bangladesh (1985-2022). *Ecological Informatics* 75: 102075. DOI: <https://doi.org/10.1016/j.ecoinf.2023.102075>
- Wang K, Franklin SE, Guo X, Cattet M. 2010. Remote sensing of ecology, biodiversity and conservation: a review from the perspective of remote sensing specialists. *Sensors* 10: 9647-9667. DOI: <https://doi.org/10.3390/s101109647>
- Wang L, Jia M, Yin D, Tian J. 2019. A review of remote sensing for mangrove forests: 1956-2018. *Remote Sensing of Environment* 231: 111223. DOI: <https://doi.org/10.1016/j.rse.2019.111223>
- Wang L, Sousa WP. 2009. Distinguishing mangrove species with laboratory measurements of hyperspectral leaf reflectance. *International Journal of Remote Sensing* 30: 1267-1281. DOI: <https://doi.org/10.1080/01431160802474014>
- Wang L, Sousa WP, Gong P, Biging GS. 2004. Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment* 91: 432-440. DOI: <https://doi.org/10.1016/j.rse.2004.04.005>
- Wannasiri W, Nagai M, Honda K, Santitamont P, Miphokasap P. 2013. Extraction of mangrove biophysical parameters using airborne LiDAR. *Remote Sensing* 5: 1787-1808. DOI: <https://doi.org/10.3390/rs5041787>
- West RC. 1956. Mangrove swamps of the Pacific Coast of Colombia. *Annals of the Association of American Geographers* 46: 98-121. DOI: <https://doi.org/10.1111/j.1467-8306.1956.tb01498.x>

- Whittaker RH, Likens GE. 1973. The biosphere and man. In: Lieth H, Whittaker RH, eds. *Primary Productivity of the Biosphere. Ecological Studies, vol 14*, Berlin, Heidelberg: Springer-Verlag, pp. 305-328. DOI: https://doi.org/10.1007/978-3-642-80913-2_15
- Woodcock CE, Strahler AH. 1987. The factor of scale in remote sensing. *Remote Sensing of Environment* 21: 311-332. DOI: [https://doi.org/10.1016/0034-4257\(87\)90015-0](https://doi.org/10.1016/0034-4257(87)90015-0)
- Wulder MA, Loveland TR, Roy DP, Crawford CJ, Masek JG, Woodcock CE, Allen RG, Anderson MC, Belward AS, Cohen WB, Dwyer J, Erb A, Gao F, Griffiths P, Helder D, Hermosilla T, Hipple JD, Hostert P, Hughes MJ, Huntington J, Johnson DM, Kennedy R, Kilic A, Li Z, Lymburner L, McCorkel J, Pahlevan N, Scambos TA, Schaaf C, Schott JR, Sheng Y, Storey J, Vermote E, Vogelmann J, White JC, Wynne RH, Zhu Z. 2019. Current status of Landsat program, science, and applications. *Remote Sensing of Environment* 225: 127-147. DOI: <https://doi.org/10.1016/j.rse.2019.02.015>
- Xie Y, Sha Z, Yu M. 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology* 1: 9-23. DOI: <https://doi.org/10.1093/jpe/rtm005>
- Yang L, Driscoll J, Sarigai S, Wu Q, Chen H, Lippitt CD. 2022. Google Earth Engine and artificial intelligence (AI): a comprehensive review. *Remote Sensing* 14: 3253. DOI: <https://doi.org/10.3390/rs14143253>
- Yang C, Everitt JH, Fletcher RS, Jensen RR, Mausel PW. 2009. Evaluating AISA + Hyperspectral imagery for mapping black mangrove along the South Texas Gulf Coast. *Photogrammetric Engineering Remote Sensing* 75: 425-435. DOI: <https://doi.org/10.14358/PERS.75.4.425>
- Yevugah LL, Osei Jr EM, Ayer J, Osei J. 2017. Spatial mapping of carbon stock in riverine mangroves along Amanzule River in the Ellembele District of Ghana. *Earth Science Research* 6: 120-128. DOI: <https://doi.org/10.5539/esr.v6n1p120>
- Zhang C, Kovacs JM, Liu Y, Flores-Verdugo F, Flores-de-Santiago F. 2014. Separating mangrove species and conditions using laboratory hyperspectral data: a case study of a degraded mangrove forest to the Mexican Pacific. *Remote Sensing* 6: 11673-11688. DOI: <https://doi.org/10.3390/rs61211673>
- Zhang Z, Fan Y, Jiao Z. 2023. Wetland ecological index and assessment of spatial-temporal changes of wetland ecological integrity. *Science of The Total Environment* 862: 160741. DOI: <https://doi.org/10.1016/j.scitotenv.2022.160741>
- Zhou X-X, Cai L-L, Fu M-P, Hong L-W, Shen Y-J, Li QQ. 2016. Progress in the studies of vivipary in mangrove plants. *Chinese Journal of Plant Ecology* 40: 1328-1343. DOI: <https://doi.org/10.17521/cjpe.2016.0087>

Associate editor: Arturo de Nova

Author contributions: DC conceived the study, performed a search of the literature, analyzed the information, and wrote the original draft; JL-P, analyzed information; JAG-C, analyzed information; JAM, conceived the study, and wrote the first draft. All authors discussed the reviewed information, contributed significantly to the manuscript, and approved the final version.

Supporting Agencies: Consejo Nacional de Ciencia y Tecnología (CONACYT), grant FORDECYT 273646, LANRESC 293354. Consejo Nacional de Ciencias y Tecnología (CONACYT), Ph.D. scholarship (CVU 508420).