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A review of remote sensing for mangrove forests: 1956–2018

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ABSTRACT

Mangrove forests are highly productive ecosystems that typically dominate the intertidal zone of tropical and subtropical coastlines. The history of mangrove remote sensing (RS) can be traced back to 1956. Over the last six decades, hot spot topics in the field of mangrove RS have evolved from mangrove distribution mapping, biophysical parameters inversion, to ecosystem process characterization. Although several review articles have been published to summarize the progress in this field, none of them highlighted the key milestones of historical developments pertinent to major research topics or key drivers that stimulate such milestones.

In this review, we aim to identify key milestones in mangrove RS by associating the emergence of major research topics with the occurrence of new sensors in four historical phases, i.e. before 1989, 1990–1999, 2000–2009, and 2010-2018. For each identified research topic, an in-depth theoretical understanding was achieved by analyses of both the first published article and the most-cited article. Based on the analyses, the current state of knowledge as well as existing limitations were summarized. In addition, in order to gain insights on driving forces for emergence of new research topics, we compared the chronological evolution of mangrove RS with that of terrestrial forest RS.

Interestingly, we found that key research topics in mangrove RS replicated those of forest RS yet with varying time lags. This can be attributed to the following two facts: 1) mangrove forests often appear as more elongated patches than terrestrial forests; 2) field work is more challenging in mangrove habitat. Along with the RS sensors' advancement, various topics that had been studied in terrestrial forests were later transformed to mangrove studies. Based on the projected growth of foreseeing earth observation capacity, insights on future research directions in mangrove RS were also presented.

1. Introduction

Mangrove forests are tropical trees and shrubs that grow along coastlines, mudflats, and river banks in many parts of the earth (Field, 1999). They are among the most productive and biologically significant ecosystems because they supply numerous goods and services to the society in addition to benefitting both coastal and marine systems (Giri et al., 2011b; Valiela et al., 2001). However, over the last two decades of the 20th century, around 35% of the world's mangrove forests has disappeared, putting mangroves in peril (Bosire et al., 2008; Valiela et al., 2001).

Because of the harsh environment in mangrove ecosystems, remote sensing (RS) has served as a sustainable tool in studies of mangrove forests (Blasco et al., 2001; Kumar et al., 2013; Vaiphasa, 2006). For several decades now, with the development of earth observation capacity, RS of mangroves was not limited to mapping their extents, but also in many complex topics, such as biophysical parameters inversion and ecosystem process characterization. To date, over 1300 scientific papers published on various topics in the field of mangrove RS, but the key milestones are not highlighted, so that the developing process, historic contributions, and drive forces are still not clear.

To our knowledge, six review papers have focused on mangrove RS since 2010 (Cardenas et al., 2017; Giri, 2016; Heumann, 2011b; Kuenzer et al., 2011; Purnamasayangsukasih et al., 2016). Among these post-2010 reviews, Kuenzer et al. (2011) provided comprehensive overview of all the sensors and methods undertaken in mangrove research, and further discussed their potential and limitations. Heumann (2011b) and Wang et al. (2018a) reviewed recent advancements in RS data and techniques and described future opportunities. Purnamasayangsukasih et al. (2016) reviewed the uses of satellite data

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in mangrove RS with the main focus on the abilities, benefits, and limitations of optical and radar imagery data. Giri (2016) gave a brief summary of the nine papers published in a special issue, and also emphasized recent improvements of mangrove RS that have been achieved in terms of RS data availability, classification methodologies, computing infrastructure, and availability of expertise. Cardenas et al. (2017) intended to challenge scientists to take advantage of all publicly available imagery, processing facilities and datasets, then emphasized the need for scientists to acquire programming skills.

These reviews could serve as good starting points for researchers who want to learn about mangroves RS. However, there still exist three critical gaps: 1) Most of the existing reviews organize papers according to data types, but not research topics. The only exception is Heumann (2011b). Regardless, the chronological evolution of research topics is not discussed. Consequently, it is hard to understand why different research topics on mangrove were proposed in the past, and more importantly, what are the potential research topics in the near future; 2) Key milestones on mangrove RS are not clear. Existing reviews are made based on a large number of published articles, which overwhelms general audience as many of them are overlapped with regards to their topics and methods. On the other hand, it is imperative to understand the main stream of research in mangrove RS. This can be only made available by identification of key milestone associated with distinctive research topic. Specifically, a) who first initiated a new topic, b) in which year, and c) which work received most attention. 3) driving forces are not mentioned. The most pressing question for mangrove RS is to predict the future potential research topics. Solution to this question can be only sought by understanding of driving forces to the existing research topics. At this point, none of the review articles attempted to reveal these forces. It's non-trivial to identifying such forces so as to project the future research topic.

Based on the above analysis, this article does not intend to make an all-embracing review, but aims to find the skeleton of mangrove RS developing process by organizing scientific papers according to their research topics in the chronological order. For each identified research topic, only the first publications and most cited article will be introduced as the key milestones, and the current state of knowledge will also be given. Thus, the objectives of this study are: 1) to identify key milestones of RS of mangrove forests to provide a historical overview of this research field in the chronological order; 2) to discover key drivers for the evolution of different milestones so as to analyze theoretical developments of mangrove RS; and 3) to project future research directions in mangrove RS.

2. Evolution of mangrove RS

We summarized the historical evolution of mangrove RS in Fig. 1, according to the research topics, RS techniques, and sensors. In the following subsections, we provide more detailed descriptions of the evolution for each decade, namely before 1989, 1990-1999, 2000-2009, and 2010-2018.

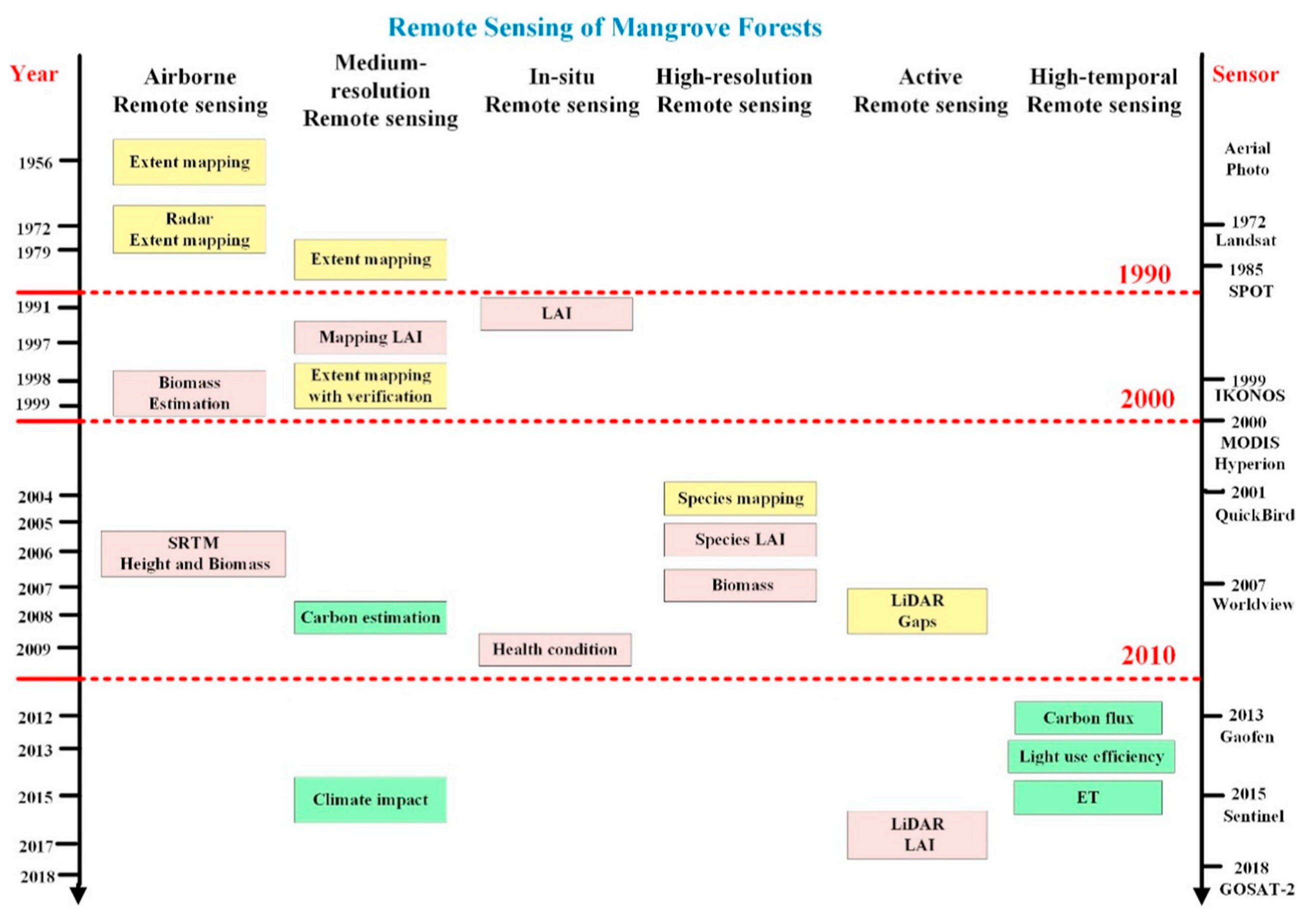

Fig. 1. Evolution of mangrove RS since 1956. Yellow, pink, and green boxes represent studies on distribution mapping, biophysical parameters inversion, and ecosystem process characterization, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

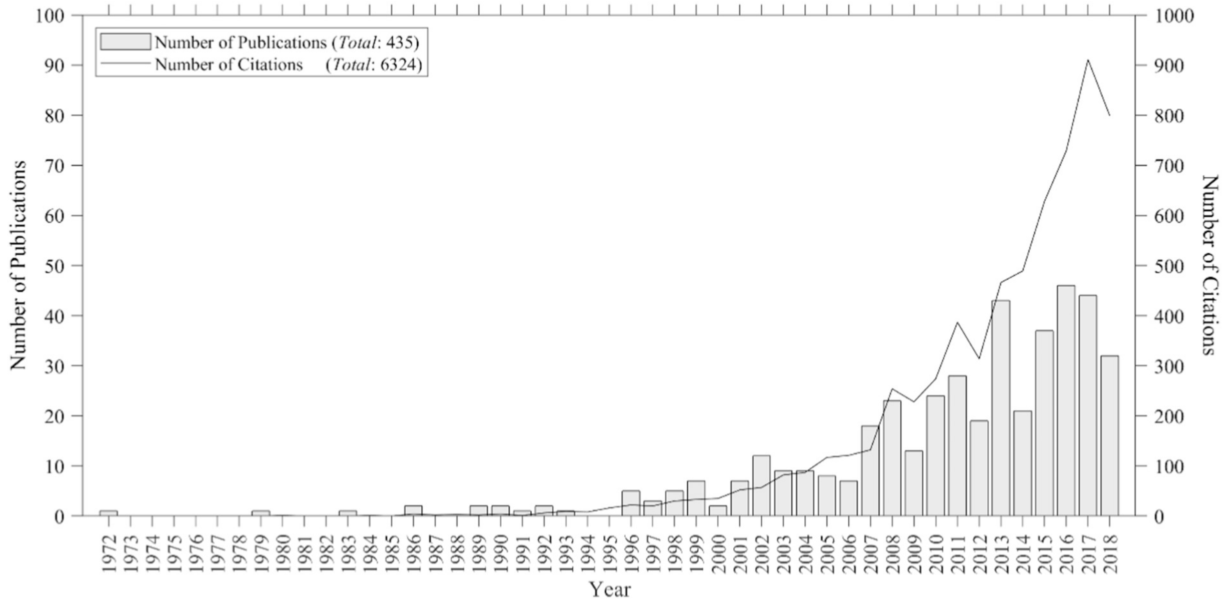

Fig. 2. Literature on RS-based mangrove extent mapping.

2.1. Before 1989, mangrove extent

Mangrove forests are highly productive ecosystems dominating the intertidal zones along tropical and subtropical coastlines (Kathiresan and Bingham, 2001; Lugo and Snedaker, 1974; Wang et al., 2004a). To effectively study mangrove areas and to monitor their changes over time, accurate, timely, and cost-effective mapping techniques are required (Green et al., 1998).

The history of mapping mangrove extent with RS data can be traced back to 1970s. Most of the mangrove extent mapping works before 1989 with RS data were conducted without accuracy assessment (Everitt and Judd, 1989; Lewis and MacDonald, 1972; Lorenzo et al., 1979).

Subsequently, two studies of mapping mangrove extent were conducted with accuracy assessment using Landsat TM, SPOT XS or airborne images during 1990–2000 (Gao, 1999; Green et al., 1998). Then, with the accumulation of RS data over the few past decades, some studies about mangrove forest temporal change detections were conducted during 2000–2010 (Fromard et al., 2004; Kovacs et al., 2001). Afterwards, Spalding et al. (2010) provided the first truly global assessment of the state of the world's mangroves. Then, several studies of mapping mangrove extent at large scale were following by using medium-low spatial resolution RS images after 2000 (Giri et al., 2015; Giri et al., 2011b; Jia et al., 2014). In 2017, Chen et al. (2017b) mapped the spatial extent of China's mangroves. The advantage of this study is that they developed a phenology-based algorithm to identify mangrove forests by analyzing a large volume of satellite images using Google Earth Engine (GEE), a cloud-computing platform.

Approximately 435 studies on mapping mangrove extent have been published to date (Fig. 2). Giri et al. (2011a) mapped the status and distributions of global mangroves using available Landsat data which leading the number of citations sharply increased. All publications can be grouped into two categories. Before 2011, most of the studies focused on mapping mangrove forest extent by exploring different types of RS data (Green et al., 1998; Kovacs et al., 2001). After 2011, studies aiming to map mangrove extent at large scales has drawn more attention (Chen et al., 2017a; Giri et al., 2011a).

2.2. During 1990–1999, mangrove LAI

Leaf area index (LAI) is one of the most important indicators for predicting photosynthesis, respiration, carbon and nutrient cycling, transpiration and rainfall interception (Doughty and Goulden, 2015; Wang et al., 2016b).

Most works on LAI estimation before 1990 used ground-based methods (Lugo et al., 1975; Weaver et al., 1986), which were extremely time consuming and difficult to acquire the large-scale spatial and temporal variability of LAI (Clough et al., 2000; Kamal et al., 2016; Sumnall et al., 2016), especially over difficult terrains, such as mangrove forests in the intertidal zone (Lagomasino et al., 2014). Most of the mangrove forests grow in relatively small patches and linear stands. The spatial resolution of existing satellite RS data (e.g. Landsat TM) before 1990 was low, which could not distinguish these details, and the results were difficult to verify (Green et al., 1997).

The emergence of high-resolution satellites image SPOT-1 after 1990 provided the possibility of mangrove LAI inversion. Ramsey and Jensen (1996) established the relationship between in-situ canopy spectra and mangrove LAI, which provided reference for the inversion of mangrove LAI from satellite data. Green et al. (1997) found SPOT and Landsat image derived NDVI (normalized difference vegetation index) in good correlation with ground measured LAI. This study mapped mangrove LAI with RS image for the first time, which has opened the door to new sources of data to effectively characterize mangrove LAI.

Approximately 64 studies on mapping mangrove LAI have been published to date (Fig. 3), most of which were after Ramsey and Jensen (1996) and Green et al. (1997). These publications mainly focused on exploring the potentials of the different types of RS data, which included in-situ hyperspectral data (Ramsey and Jensen, 1996), high-resolution imagery (Kovacs et al., 2004; Kovacs et al., 2005a), medium resolution imagery (Ramsey and Jensen, 1996), airborne hyperspectral data (Green et al., 1998), radar data (Kovacs et al., 2008c), and most recently unmanned aerial vehicle (UAV) multispectral images (Tian et al., 2017).

2.3. During 2000–2009

With the preliminary problem of extent mapping solved to some extent by 1999, the hotspot of mangrove RS studies during 2000–2009 turned to more detailed characterizations, specifically, species classification, vertical structure mapping (height, biomass and carbon stock), and health condition retrieval. The solution of these problems has

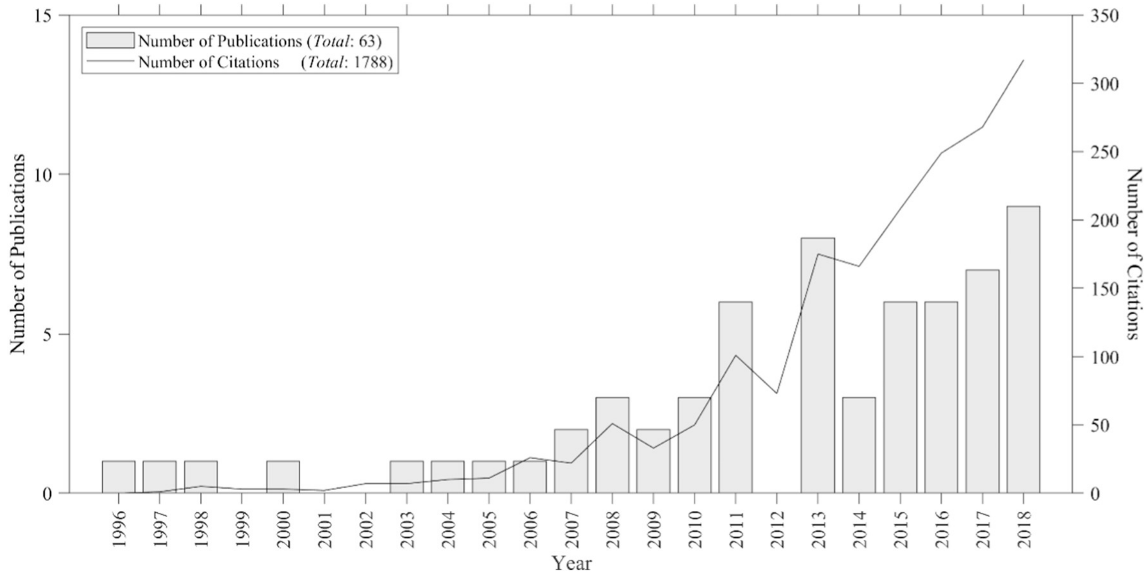

Fig. 3. Literature on RS-based mangrove LAI estimation.

largely benefitted from the launching of new spaceborne RS sensors, especially those providing global high spatial resolution data.

2.3.1. Species classification

In the previous decade, most research focused on mangrove extent mapping, but was not able to distinguish different mangrove species. The major obstacle is that mangroves of one species usually form narrow strips or small patches, thus not identifiable in satellite images (Blasco et al., 1998; Green et al., 1998). Airborne high resolution data, although reported useful for mangrove species classification (Held et al., 2003; West, 1956), is site-specific and not available to all areas. The launching of high spatial resolution satellite sensors since 1999 has enabled the efficient mapping of mangrove species in large areas.

Wang et al. (2004a) was the first research to successfully classify mangrove species. Using IKONOS 1-m panchromatic and 4-m multispectral images, three mangrove species (i.e. red, black, and white mangroves) along the Caribbean coast of Panama were separated with 70%–98% accuracy. This study demonstrated the necessity of integrating object-based image analysis (OBIA) into mangrove species classification, and has been the most influencing publication on this problem. The critical issue of optimal scale parameter selection for object segmentation was solved by searching for the highest classes' separability (Wang et al., 2004a). In addition, a comparison between the first high resolution satellites images found that better accuracy was achieved using IKONOS than QuickBird while QuickBird is more affordable (Wang et al., 2004b).

Approximately 310 species-level mangrove RS studies have been published to date (Fig. 4), most of which were after Wang et al. (2004a) and Wang et al. (2004b). Starting from 2011, the number of publications start to take off, marking the recognition of mangrove species mapping as a mature procedure. These publications can be grouped into three categories. First, one type of works continued on improving mangrove species classification by modifying the algorithm or using new data (Heumann, 2011a; Myint et al., 2008). Second, some studies investigated for different mangrove species the other parameters such as LAI (Kovacs et al., 2005b). Furthermore, with species-level information available, multi-temporal analysis are implemented to study the dynamics of mangroves at individual species level (Ghosh et al., 2016; Satyanarayana et al., 2011).

2.3.2. Vertical structure and biomass

After achieving some success on mapping the horizontal extent of mangroves in the past three decades, the hotspot of mangrove study has turned to the retrieval of 3D parameters, more specifically the estimation of height and biomass. Biomass, generally defined as the amount of organic matters, can be further used to estimate carbon stock, which is the quantity of carbon in mangroves (http://www.fao.org/docrep/007/ae156e/AE156E03.htm#P240_10382).

The correlation between mangrove structure parameters and RS data (e.g. spectra, radar) has been found significant last century (Mougin et al., 1999; Ramsey and Jensen, 1996). On this basis, researchers have tried to retrieve the structure and biomass of mangroves using airborne data (Lucas et al., 2002). However, large scale mapping of mangrove vertical structure has been lacking due to the high density of mangrove trees and roots as well as their flooded habitats.

Simard et al. (2006) successfully estimated mean tree height and biomass in the Everglades National Park in south Florida using shuttle radar topography mission (SRTM) elevation data and has been the most cited publication on this topic. By calibrating the SRTM elevation with airborne LiDAR data using a quadratic function, mean mangrove height was estimated with 2.0 m RMSE (root mean square error). Subsequently, stand level biomass was estimated from mean height using the linear allometric equation constructed from field surveyed biomass and tree height.

To date, 71 articles worked on mangrove height and 157 worked on mangrove biomass, the most of which overlap (Fig. 5, Fig. 6). Mangrove height is estimated from a canopy height model, which is usually derived from LiDAR data where height is directly measured (Chadwick, 2011) or image stereopairs where 3D model can be constructed (Lagomasino et al., 2015a). With height information available, biomass is then estimated from height using predefined allometric equations (Chadwick, 2011; Fatoyinbo et al., 2008). To improve the accuracy of biomass estimation, effort has been put into constructing better allometric equations (Olagoke et al., 2016). In addition, the uncertainty analysis of mangrove height products has also drawn attention (Lagomasino et al., 2016). Another approach to estimate mangrove biomass followed the inspiration by Mougin et al. (1999) and Lucas et al. (2002), and estimated biomass according to its relationship with spectral reflectance or radar backscattering parameters (Li et al., 2007; Pham et al., 2018; Proisy et al., 2007).

2.3.3. Carbon stock estimation

Mangrove carbon stock refers to the amount of carbon stored in mangroves. Depending on the specific task, the 'carbon stock' can mean

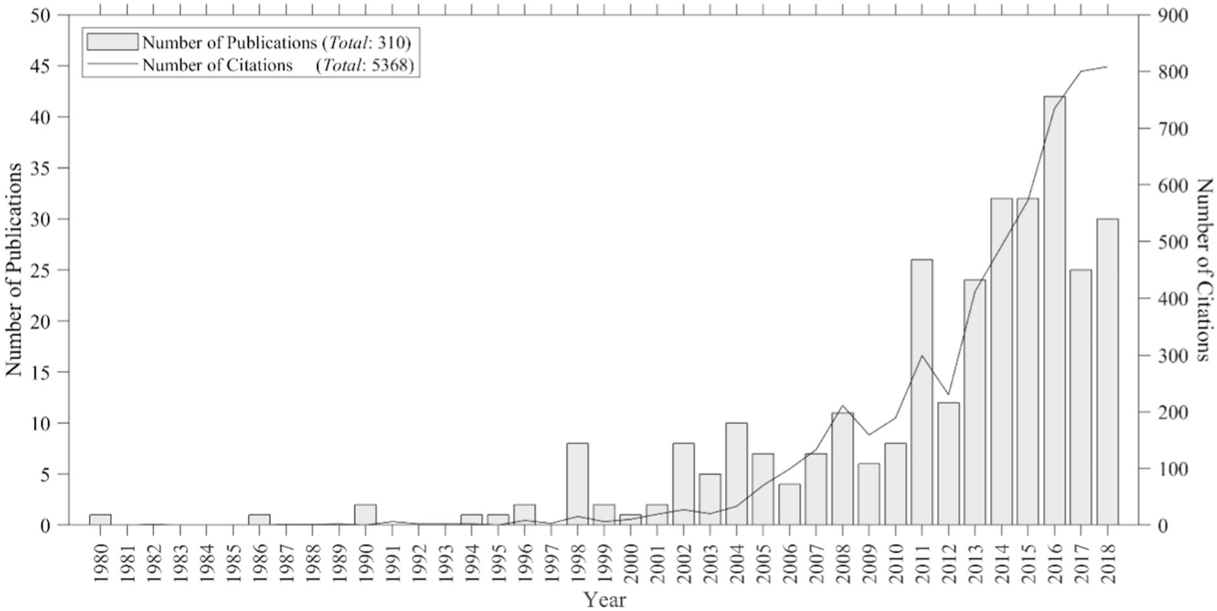

Fig. 4. Literature on RS-based mangrove species classification.

carbon in the mangrove plants (i.e. 'biomass carbon stock') or carbon in the mangrove ecosystems (i.e. biomass carbon plus carbon in soil and sediments).

With the increasing awareness of mangroves as an effective long-term carbon sink, the impact of mangroves on global carbon dynamics becomes more and more recognized (Chave et al., 2005; Donato et al., 2011). As a result, mangrove RS started to estimate the carbon stock. In the new decade, the systematic study of mangrove carbon stock estimation has developed as a new branch in mangrove RS studies.

Fatoyinbo et al. (2008) tried to estimate mangrove biomass carbon stock, assuming that 50% of the dry biomass is carbon. With the biomass estimated from SRTM derived tree heights, the biomass carbon stock was assessed. However, the accuracy was not assessed. Wicaksono et al. (2011) was the first study that focused on the carbon stock mapping of mangrove ecosystems. Both above ground carbon (AGC) and below ground carbon (BGC) were calculated from Landsat ETM+ imagery. After comparing different vegetation indices and mangrove fraction derived by spectral unmixing, the maximum accuracy was achieved using the linear regression with global environment monitoring index (GEMI). For AGC, 62% variation of carbon stock was explained, with standard error of 93.5 Tg C/ha. For BGC, 56.18% variation of carbon stock was explained, with standard error of 26.98 Tg C/ha.

Although still in the emerging stage, publications on mangrove carbon using RS have reached 90 (Fig. 7). Following Fatoyinbo et al. (2008), one approach is to estimate biomass carbon stock by assuming 45%–50% of the biomass is carbon (Patil et al., 2014). Most studies used this to provide carbon estimate from field surveyed biomass to provide reference data (Friess et al., 2016; Wicaksono et al., 2011). On the other hand, following Wicaksono et al. (2011), one approach is to estimate carbon stock using regression models from vegetation indices and parameters (Friess et al., 2016; Wicaksono et al., 2016).

2.3.4. Health conditions retrieval

Mangroves are considered the most productive in all ecosystems, presuming that they are in good health condition (Ramsey and Jensen,

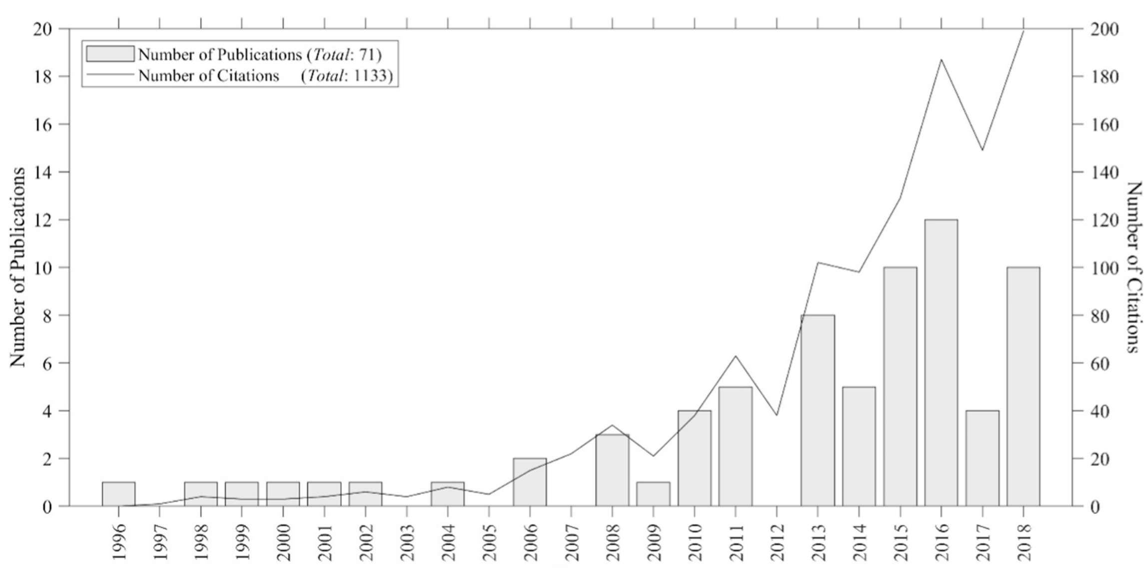

Fig. 5. Literature on RS-based mangrove height estimation.

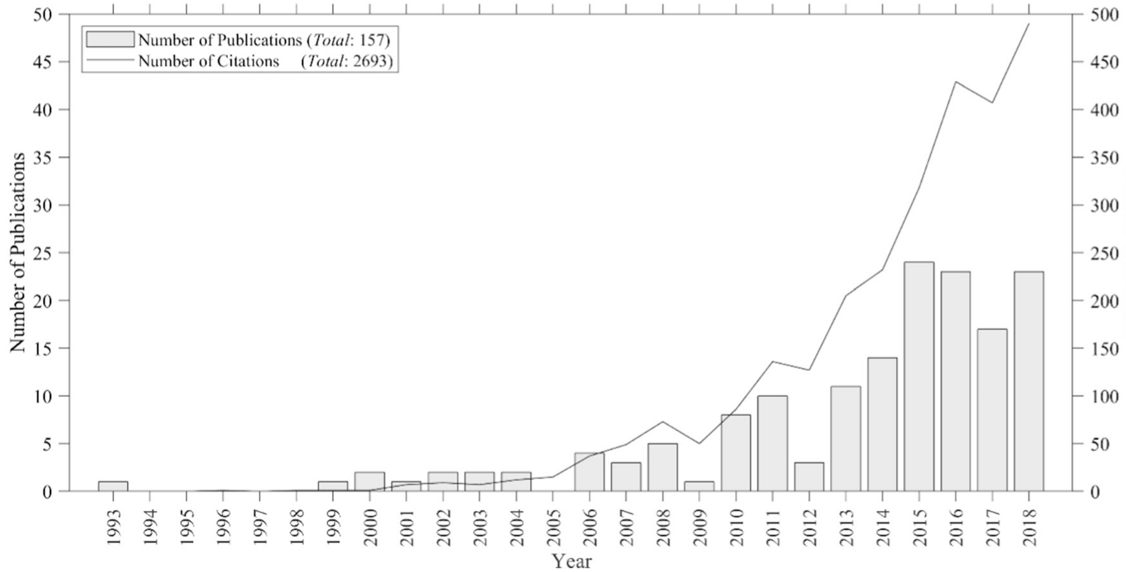

Fig. 6. Literature on RS-based mangrove biomass estimation.

1996). However, when temperature, salinity and other factors are suboptimal, mangrove plants become stressed, thus their function as the "coastal kidney" gets hampered.

It has long been noticed that mangroves of different health conditions can be differentiated from radar (Kovacs et al., 2005b). However, the health of mangroves depends on a set of climatological and tidal variables and their interactions (Imhoff et al., 1986). As a result, little attention has been put to monitoring health conditions of mangroves.

Kovacs et al. (2008a) concluded that multi-polarized spaceborne synthetic aperture radar (SAR) could be used to distinguish healthy and degraded mangroves because a significant correlation between the backscattering coefficients of ENVISAT SAR and LAI was found ($R^2 = 0.82$). LAI was used as the indicator of mangrove health because a distinctive increase of LAI was noticed from the sample white mangrove plots of dead (LAI~0), poor (LAI~1) and healthy conditions (LAI~2.3). In terms of spectral reflectance, Wang and Sousa (2009) found out the difference in leaf reflectance between healthy and stressed mangroves. Four band ratio indices (R695/R420, R605/R760, R695/R760, and R710/R760) were constructed using narrow band reflectance from laboratory hyperspectral measurements. ANOVA revealed that these indices can effectively distinguish healthy and stressed mangroves of the same species (red, white, and black mangroves).

Only 78 studies have been published regarding health conditions of mangroves (Fig. 8), which can be separated to two different approaches. First, following Kovacs et al. (2008a) and Wang and Sousa (2009), vegetation indices and parameters derived from hyperspectral or radar data were used as proxy of mangrove health condition. These indices include but are not limited to LAI, photochemical reflectance index (PRI) (Song et al., 2011), NDVI (Chellamani et al., 2014), percent tree cover (PTC) (Ishtiaque et al., 2016), enhanced vegetation index (EVI) (Ishtiaque et al., 2016), and leaf Chl-a concentration (Flores-de-Santiago et al., 2013). Second, classification methods have also been used to distinguish mangroves of different health status (Vidhya et al., 2014; Zhang et al., 2014; Zhang et al., 2013).

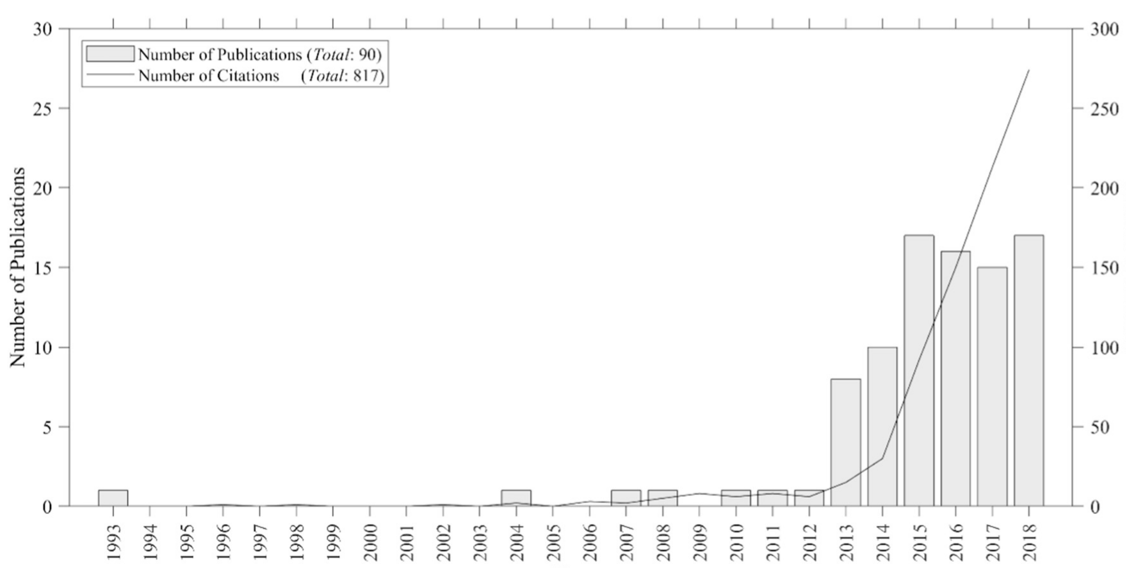

Fig. 7. Literature on RS-based mangrove carbon stock estimation.

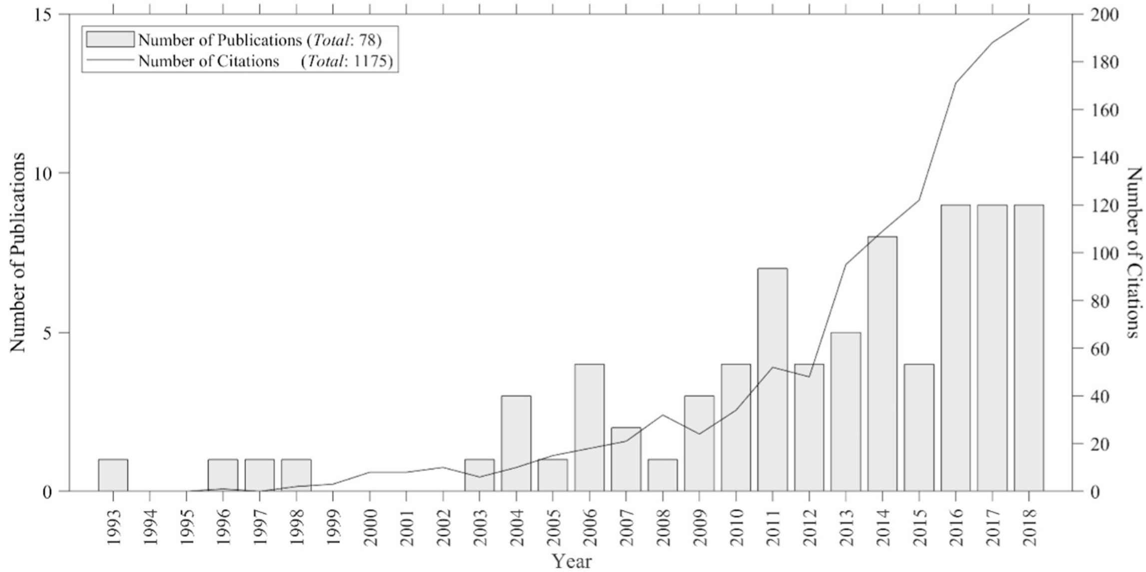

Fig. 8. Literature on RS-based mangrove health assessment.

2.4. During 2010–2018

With the extensive ongoing studies of RS-based mangrove forests (species) mapping and structure inversion, results of mangrove extents, species distributions, and primary parameters are accurate enough to carry out further research. At the same time, the development of mangrove ecological functions and global climate change research has pushed the RS-based mangrove analyses to a comprehensive level. From 2010 to 2018, the most significant improvement of RS-based mangrove research is that mangroves are considered as a coupled ecosystem participating in global carbon cycling and energy balance, and responding to global climate change. These new studies can be concluded to three topics as follows.

2.4.1. Carbon fluxes

Carbon flux, defined as the rate of exchange of carbon between pools (reservoirs), directly refers to the global carbon cycling. Due to the high rates of carbon sequestration ($1.5\,\mathrm{Tg\,C\,ha^{-1}\,yr^{-1}}$) and the specific position at the terrestrial-ocean interface (potential exchange with coastal waters), mangrove forests are considered to have a unique contribution to global carbon cycling and received significant attention in carbon fluxes research (Bouillon et al., 2008; Eong, 1993; Twilley et al., 1992).

However, until now only 12 papers focused on RS-based mangrove carbon fluxes (Fig. 9). This limited amount is a combination result of challenges associated with in situ flux studies (there is only one mangrove flux tower site available in the Fluxnet website, http://fluxnet.fluxdata.org/) and rarely accessible high temporal resolution RS data.

In 2012 and 2013, tower-based CO_2 eddy covariance (EC) in conjunction with EVI derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) were utilized to estimate seasonal and annual CO_2 fluxes and canopy-scale photosynthetic light use efficiency of mangrove forests in Florida Everglades (Barr et al., 2013; Barr et al., 2012). The model developed in these studies provided the first framework for estimating CO_2 fluxes of mangroves using RS data and environmental factors.

In 2013, Zulueta et al. (2013) measured CO_2 fluxes of mangroves, desert, and marine ecosystem from an aircraft which incorporated

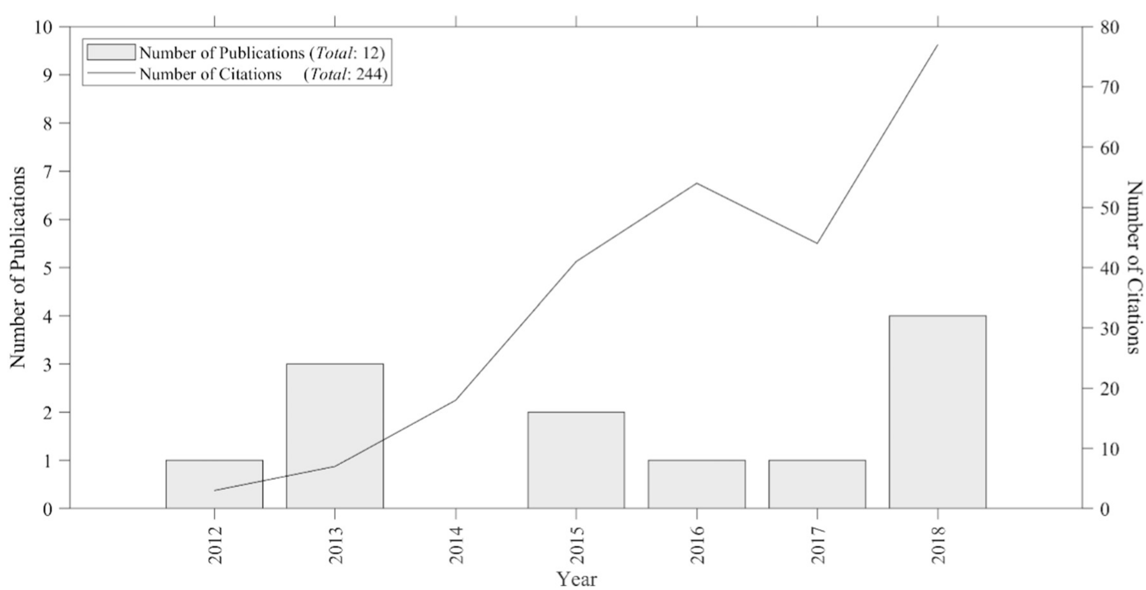

Fig. 9. Literature on RS-based mangrove carbon flux characterization.

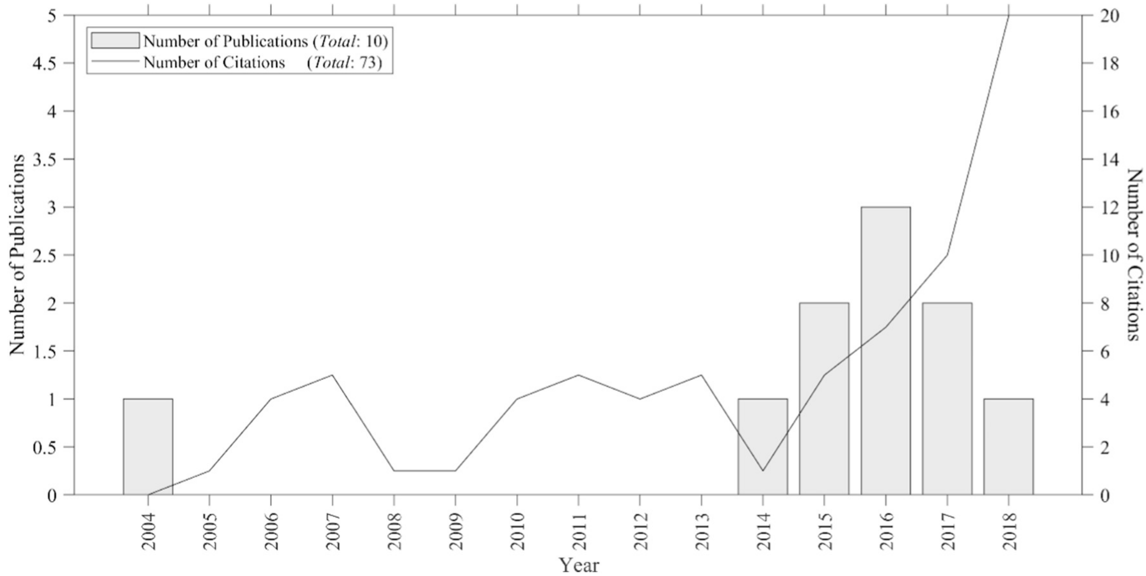

Fig. 10. Literature on RS-based mangrove echohydrology.

instrumentation for eddy covariance measurements (mobile flux platform) and low-level RS. They concluded that mangroves showed the highest uptake of CO_2.

2.4.2. Ecohydrology

Evapotranspiration (ET) is the sum of evaporation and plant transpiration from the Earth surface to the atmosphere. RS has proved to be an effective tool for estimating ET rates and other energy balance parameters in different ecosystems such as agricultural lands (Boegh et al., 2002) and terrestrial forests (Chen et al., 2005). However, due to the limitation of data source, very limited studies focused on RS-based estimation of mangrove ET and other energy balance parameters (Fig. 10).

In 2015, Lagomasino et al. (2015a) combined long-term datasets acquired from Landsat TM and the Florida Coastal Everglades Long-Term Ecological Research project to investigate ET, latent heat, and soil heat flux of mangrove ecotone in the Everglades. Modeled results from Landsat data were calibrated and tested using the environmental and meteorological parameters collected from the eddy-covariance tower and weather tower, providing relationships between energy and water balance components which also applied to other mangrove systems.

2.4.3. Impact of climate change on mangroves

Threats to the mangroves from changes in sea-level and temperature are the greatest compared to other factors such as atmospheric composition and land surface alterations (Alongi, 2002).

According to Alongi (2008), mangroves would be set landward or disappear due to the continuous rise in sea-level and no change in sedimentary. Furthermore, most mangroves would be degraded, because the areas for mangrove landward migration are already occupied by man-made structures such as ports, dams, and ponds in many parts of the world (Jia et al., 2015, 2018).

However, until now only two RS-based research provided particular discussion on how climate factors impacted mangroves. Due to the lack of long-term continuous climatic variables dataset (for example, the sea-level rise records is only available from 1993), most studies did not analyze the relationship between climate change and mangroves (Fig. 11).

In 2015, Srivastava et al. (2015) integrated RS data and meteorological data to assess the impacts of climate change on the mangrove ecosystem. Their results showed that (1) rainfall and sea-level rise significantly affected the extent and density of mangrove species, (2) mean sea level and wind speed were inversely related to mangrove area, and (3) increment of temperatures could cause the mangrove extent to decrease. In 2018, Pastor-Guzman et al. (2018) presented the first regional characterisation of mangrove phenology, and concluded that cumulative rainfall in cold and dry season has a direct impact on mangrove phenology.

3. Discussion (analysis of key drivers for the evolution and current limitation)

As a unique type of forest, mangroves are found along the coasts of tropics or subtropics, occupying only 0.4% of global forests (FAO, 2010). To detect driving forces of mangrove RS development, we assume that research of mangrove RS have certain relations with research of forest RS. In total, 1208 mangrove RS papers and 37,152 forest RS papers were published to date (Fig. 12). Basically, current literatures on mangrove RS can be divided into three sub-fields depending on the complication of ecological issues that can be addressed by RS applications: (1) mangrove distribution mapping, (2) biophysical parameters inversion, and (3) ecosystem process characterization (Fig. 13). This study compares the evolution of mangrove RS with terrestrial forest RS in the abovementioned three aspects.

3.1. Mangroves distribution mapping

Vegetation distribution mapping is a traditional and essential task of RS. According to our literature survey, mangroves distribution mapping can be concluded into two stages: extent mapping (mangroves or non-mangroves) and species distribution mapping.

Historically, extent mapping of both mangroves and terrestrial forests were first conducted using aerial photography before 1970 (Aldrich et al., 1959; Colwell, 1964). Then, the development of satellite sensors promoted extent mapping to individual species level. Terrestrial forests species mapping started from early 1970s, but studies with acceptable classification accuracy (over 80%) were published around 1985 by interpreting Landsat TM imagery (Moore and Bauer, 1990; Shen et al., 1985; Toll, 1985). Although terrestrial forests species can be distinguished from Landsat TM, these data were unable to discriminate mangrove species (Green et al., 1998). This is probably due to the coarse spatial resolution of Landsat TM (30 m) and the patchy growth forms (narrow strips or small patches usually less than 30 m wide) of mangrove stands. The first high accurate mangrove species mapping

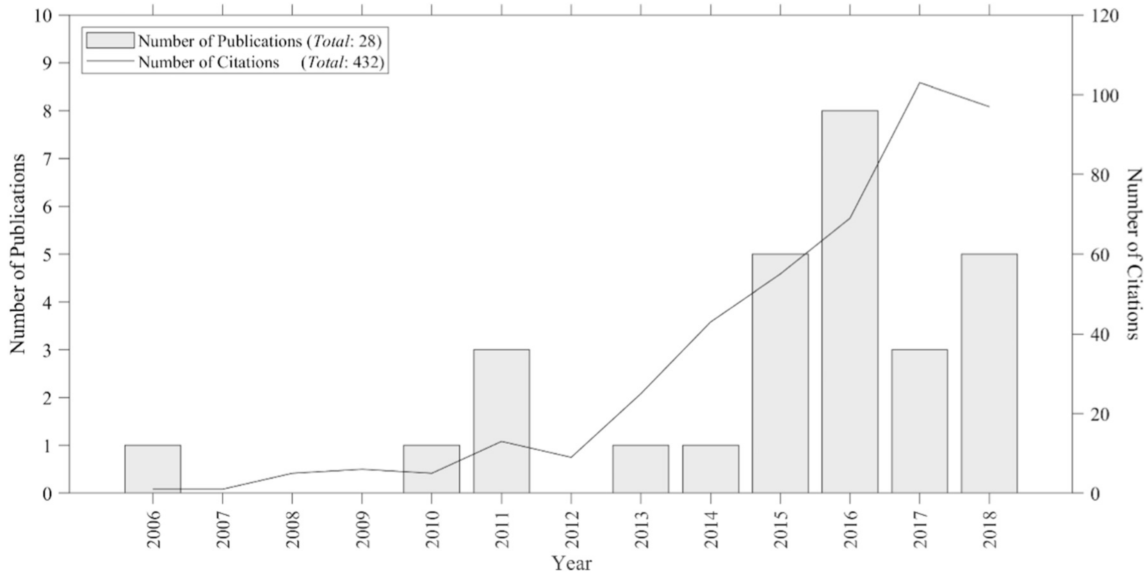

Fig. 11. Literature on RS-based studies of climate impact on mangroves.

paper was published after the launch of high resolution satellite sensors (IKONOS in 1999, QuickBird in 2001), Wang et al. (2004a) used high resolution satellite imagery of IKONOS to map mangroves species in Punta Galeta, Panama, and achieved an average accuracy of 91.4%. Vast mangrove species mapping research have appeared since the successful of this study, most of which are based on high resolution satellite imagery (Dahdouh-Guebas et al., 2005; Everitt et al., 2008).

Therefore, we conclude that the huge time lag between terrestrial forest species mapping and mangrove species mapping is caused by the availability of proper RS data. In other words, the development of mangrove distribution mapping is driven by sensor progress.

3.2. Biophysical parameters inversion

Forests biophysical parameters are important for studies of the carbon cycle and global climate (Disney et al., 2006). According to our literature survey, mangroves biophysical parameters inversion can be concluded into two types: LAI inversion, and biomass estimation.

The time lag between the first remote-sensing-based terrestrial forests LAI research and the first mangrove LAI research was not long. The first RS based study focused on forest ecosystem was published in 1987 (Peterson et al., 1987). Shortly after this, Jensen et al. did an intensive in situ sampling of mangroves in Florida in 1988, and related mangrove canopy LAI to a vegetation index generated from the SOPT XMS sensor (Jensen et al., 1991).

RS based terrestrial forests biomass estimation started from 1987. Wu (1987) suggested a potential application of multipolarization SAR data for pine-plantation biomass. Mangrove biomass estimation was first published by Mougin et al., 1999, using multifrequency and multipolarization Polarimetric AIRSAR data to retrieve information on the structure and biomass of mangroves in French Guiana. Although mangroves' high productivity and essential role in supplying organic materials to coastal ecosystems was conscious since 1980s (Hutching and Saenger, 1987), the time lag between studies of terrestrial forests biomass and mangrove biomass is notable (over 10 years). This lag can be explained in two aspects: first is the lack of fundamental ground truth

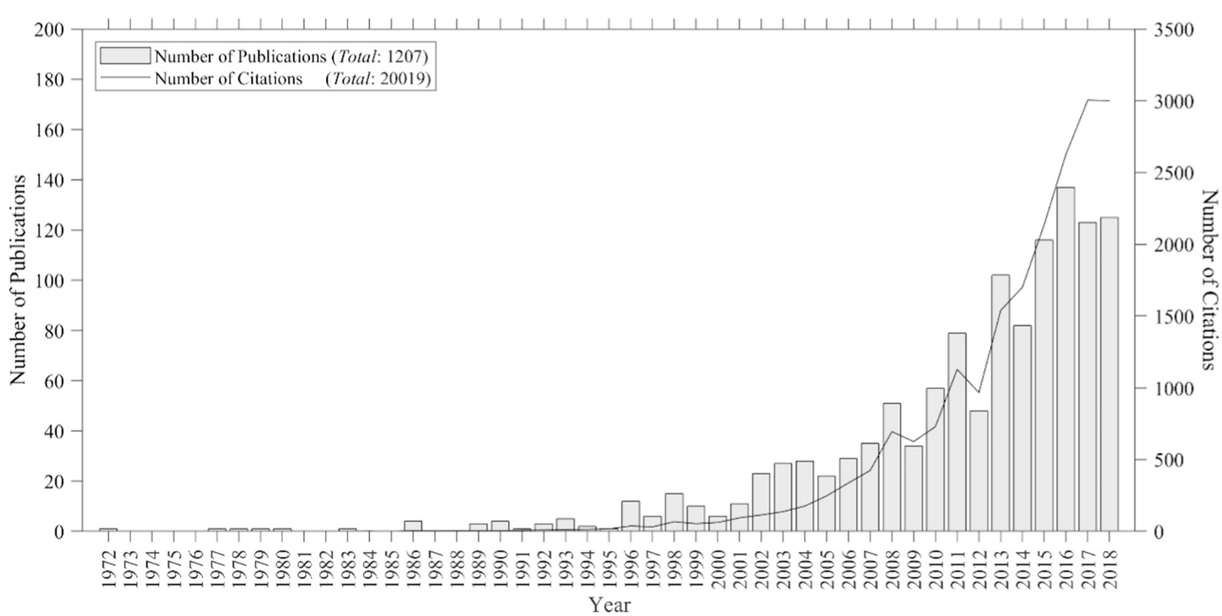

Fig. 12. Literature on mangrove RS.

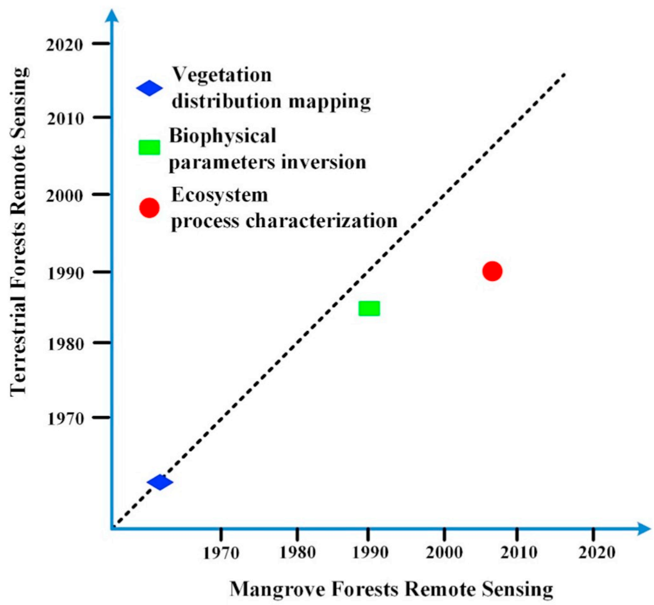

Fig. 13. Temporal relationship between mangrove RS and terrestrial forest RS.

information due to the numerous difficulties encountered during field studies in coastal environments (Mougin et al., 1999); second and the most important is the lack of proper RS data (Mougin et al. (1999) used airborne data which is rarely acquired).

Therefore, we conclude that the time lag between terrestrial forest biophysical parameters inversion and mangrove biophysical parameters inversion is caused by the availability of proper RS data. In other words, the development of mangrove biophysical parameters inversion is driven by sensor progress.

3.3. Ecosystem process characterization

Critical research problems involving forest response to global change require characterization of ecosystem processes (Running et al., 1989). Current RS based research of mangrove ecosystem processes include carbon fluxes and evapotranspiration (ET).

Studies of RS-based estimation of terrestrial forests ecosystem processes were published since the late 1980s. Running et al. (1989) mapped regional forest ET by combining satellite data (AVHRR/NDVI) with ecosystem simulation. Waring et al. (1995) used seasonal RS data (acquired by ultralight aircraft) and longtime meteorological data (acquired by meteorological sensors installed at the top of a 30 m tower) to estimate forests CO_2 exchange in Harvard Forest. Although many field and greenhouse studies have investigated the rate and mechanisms of mangrove productivity, to date only a few studies have been conducted to use RS for the estimation of carbon and water exchanges in mangrove ecosystems. The first studies focusing on mangrove's carbon fluxes and ET were published in 2012 and 2015, respectively (Barr et al., 2012; Lagomasino et al., 2015b). Both studies were conducted based on long term medium resolution RS data and carbon fluxes tower data acquired from the only mangrove tower in Everglades National Park. The huge time lag between terrestrial forests and mangrove forests can be explained in three aspects: 1) The total area of mangroves is small, occupying only 0.4% of global forests (FAO, 2010; Giri et al., 2011b). As a result, their role in global carbon cycle was neglected in the early time. 2) Traditional high temporal resolution satellite data with coarse spatial resolution, such as AVHRR, were not suitable for mangrove studies, because mangrove pixels in these images are often mixed with other coastal land covers. 3) Ecosystem process characterization needs amount of field work, especially long term critical field measurements of carbon and water fluxes. To date, there are 177 terrestrial forest carbon fluxes towers enrolled in FLUXNET with the first tower built in 1990. However, there is only one mangrove carbon fluxes tower which was built in 2003 (http://fluxnet.fluxdata.org/).

Therefore, we conclude that the time lag between terrestrial forest ecosystem process characterization and mangrove ecosystem process characterization is caused by the availability of carbon fluxes tower and appropriate RS data. In other words, the development of ecosystem process characterization is driven by data accessibility.

4. Future opportunities

As discovered in the previous section, sensor advancement has led to emergence of key milestones in the history of mangrove RS. Although a significant number of remote sensors have been launched in the last decades, an unparalleled amount of new sensors have been set forth to launch in the years to come. As such, in the following section, we share our insights on how new opportunities will arise for six existing research topics as well as a new one.

4.1. Extent mapping

Mangrove forests mapping (mangroves or non-mangroves) is the basis of other mangrove RS topics. Although extent mapping has been studied for more than 60 years, there are still great challenges and opportunities. In our opinion, two major improvements can be made in the future research.

(1) Conducting dense-temporal and fine-spatial resolution global mapping.

In 2011, Giri et al. (2011b) mapped global mangrove forests for the first time using RS images, which demonstrated substantial advancement toward global mangrove monitoring efforts. In 2016, Hamilton and Casey (2016) created a 30 m spatial resolution annual global mangrove database from 2000 to 2012. However, the spatio-temporal resolution is rather coarse.

Two recent developments in the earth observation sector have the potential to significantly improve the efficacy of mangrove monitoring across the globe. First, the European Sentinel-2A and −2B satellites comprise the global multi-spectral mission whose data is open to the global public. Launched by the European Space Agency (ESA) in June 2015 and March 2016, respectively, these two satellites provide 5-day repeat and 10 m spatial resolution imagery globally, enabling high spatio-temporal monitoring of mangrove forests (Verhegghen et al., 2016; Xiong et al., 2017). Second, the novel computing platform of GEE, which houses a complete and continually updated archive of preprocessed Sentinel-2 data, has enabled the efficient development of global-scale data products (Chen et al., 2017a; Gorelick et al., 2017).

(2) Considering the tidal influences.

Mangrove extent monitored by satellite RS could be varied depending on the instantaneous tidal level at the time satellite images were taken (Cardenas et al., 2017; Giri et al., 2007; Saito et al., 2003). Although this limitation has been proposed for more than 15 years, we still lack understanding about how tidal level affects the reflectance of mangrove forests.

In recent years, the wide use of flexible UAV offers great opportunities to quantitatively address the effects of tidal height on spectral reflectance. UAVs can be used to acquire images of mangroves at almost any time during local flood and ebb tide. Therefore, we could estimate mangrove extent by combining spectral reflectance from satellite images and instantaneous tidal height from UAV. Furthermore, if so, current mangrove maps would be effectively improved. It should be noted that UAVs also have disadvantages such as limited aerial extent and relatively lower steadiness compared to other RS platforms (Tian et al., 2016a; Yin and Wang, 2019). So we recommend using UAV to collect data at small areas to facilitate large-scale projects.

4.2. Species mapping

Composition and distribution of mangrove forest species are essential for conservation efforts and further mangrove investigation (Jia et al., 2018). In our opinion, two major improvements are feasible.

(1) Continental- or global-scale species distribution mapping.

To date, all mangrove species mapping studies were conducted in local scales, but continental or global-scale species distribution results are unavailable. There are two major barriers. First, due to the frequent clouds and cloud shadows in the mangrove swamps, high quality fine-resolution RS data that fully cover a large-scale are difficult to acquire, even commercially. Second, operating algorithms on a large number of image archives requires specialized expertise and software, powerful computing facilities, and significant time dedication (Alonso et al., 2016).

Two recent developments in the earth observation sector have the potential to significantly improve large scale mangrove species mapping. First, better multi-source data can be combined. Dense series of multispectral satellite data (e.g. Landsat-8, Sentinel-2) provide a good basis for the large-scale mapping of mangrove forest composition (Wang et al., 2018b), while further data may be added from recently launched SAR missions such as Sentinel-1 SAR. Although significant increase in accuracy is not guaranteed by adding SAR, the free availability of most of the data could be a motivation to investigate toward such approaches. Second, the novel cloud computing platform of GEE, with its large archive of pre-processed satellite datasets and its powerful parallel computing capacity, further facilitates large-scale mangrove species mapping.

(2) Distinguishing more mangrove forest species.

Globally, there are over 100 species of mangroves. Vaiphasa et al. (2007) proved that at least 16 mangrove species could be distinguished by six hyperspectral channels. However, in most published RS applications, no more than five species were discriminated. The recently available dense series of multitemporal Landsat-8 and Sentinel-2 data better capture mangrove phenology (Pastor-Guzman et al., 2018), which could possibly assist species discrimination. However, whether phenology information can be used to reliably identify mangrove species remains a question to be explored.

(3) Building a spectral library.

The spectral characteristics of different mangrove species have not been fully defined. Therefore, to assist the species classification, we call for researchers in mangrove RS to collectively build a definitive spectral library of mangrove species under various environmental conditions. It should be noted that mangroves under some environment conditions are not accessible. To collect the hyper-spectra of those mangroves, we suggest mounting high resolution hyperspectral sensors on UAVs. Nevertheless, UAV hyperspectral RS is an emerging protocol, the robustness of which still needs improvement.

4.3. LAI

LAI is one of the most significance indicator of primary productivity in mangrove wetland ecosystem, associated with many biological and physical processes of mangrove. Current RS-based methods for retrieving LAI can be grouped into two categories according to the types of RS data: passive optical and active LiDAR. However, both of them remain critical obstacles for the inversion of mangrove LAI.

(1) Passive optical RS-based methods.

Although successful inversion of mangrove LAI with passive optical RS images have been reported in many studies (Carlson and Ripley, 1997; Chen et al., 2002; George et al., 2018; Kamal et al., 2016), the challenges associated with the interference from complex background and various mangrove species have not been effectively controlled yet. Most of the existing studies applied to extracting LAI has the common characteristics that the species is singular and the background is homogeneous. However, in the mangrove forest, it is likely that both of the background and species are various.

UAV platforms provide various types of very high spatial resolution RS data at flexible acquisition time intervals (Bhardwaj et al., 2016; Hardin and Jensen, 2011; Liu and Wang, 2018), which offers terrific opportunities to eliminate the effects of background and species in the estimation of mangrove LAI (Guo et al., 2018; Tian et al., 2017). In addition, some satellite RS images (e.g. Sentinel-2) at relatively lower spatial resolution but higher spectral resolution than UAV images also have great potentials for solving the background and species issues (Wang et al., 2016a).

(2) LiDAR RS-based methods.

Airborne LiDAR can provide detailed forest vertical dimension information estimation (Chen et al., 2007; Popescu et al., 2011). However, it is often logistically difficult to use airborne LiDAR for multi-temporal and large-scale forest monitoring. The first spaceborne LiDAR system, Geoscience Laser Altimeter System (GLAS), has been successfully used for collecting repetitive and extensive forest LAI (García et al., 2012; Tian et al., 2015; Tian et al., 2016b). To the best of our knowledge, GLAS has not been applied on retrieval of mangrove LAI to date because of its sparse spatial distribution. Ice, Cloud, and land Elevation Satellite-2 (ICESat2) and Global Ecosystem Dynamics Investigation (GEDI) LiDAR have been launched in 2018, which will generate a large amount of spaceborne LiDAR data at a frequent revisit (Nie et al., 2018). Therefore, it is worthwhile to explore new methods for estimating mangrove LAI at a continental- or global-scale with spaceborne LiDAR data in the near future.

It should be noted that, besides the passive optical RS-based and LiDAR RS-based methods, radar data was also utilized for mangrove LAI inversion in some existing studies, e.g. (Kovacs et al., 2008b). However, the high moisture content in mangrove forests has hindered research on leaf area index inversion with radar data.

4.4. Structure, biomass, and carbon stock

The main obstacles for RS-based retrieval of mangrove structure, biomass and carbon stock include: (1) only a small number of structure parameters (mainly height) are estimated; and (2) ground truth data is hard to collect.

We consider that the research can be improved in the following three aspects.

(1) Individual tree characterization.

Individual tree detection methods have been widely used to count and measure individual trees to build forest inventory datasets, but are rarely applied to mangrove studies (Edson and Wing, 2011; Hirata et al., 2010; Yin and Wang, 2016). Previous studies have shown that individual tree characterization can increase the accuracy of forest parameter estimation (Hyyppä et al., 2001; Xu et al., 2014). Therefore, to assess mangrove structure and biomass at individual tree level may lead to great improvement of mangrove parameter estimation, but has largely been limited by the relatively low spatial resolution of datasets (Heenkenda et al., 2015; Kamal and Johansen, 2017; Wannasiri et al., 2013). With the increased spatial resolution of RS data, especially the use of UAVs, individual mangrove characterization is worth investigating. Recently, the first UAV LiDAR-based individual mangrove delineation work has been published (Yin and Wang, 2019). Yet more individual mangrove studies are encouraged to test the robustness of the algorithms and to improve the accuracy.

(2) Retrieving more structural parameters.

LiDAR technique has been quickly advancing, with increased point density and decreased cost (Guo et al., 2017). Therefore, mangrove structure can be represented with more details. If more parameters besides tree height (e.g. crown size, diameter at breast height) are retrieved from the LiDAR datasets, the 3D structure of mangroves can be described more comprehensively, which may furthermore lead to improved estimation of biomass and carbon stock (Lim et al., 2003).

(3) Ground truth datasets.

The estimation of biomass and carbon stock rely heavily on allometric equations (Chadwick, 2011; Fatoyinbo et al., 2008). Because the accurate measurement of biomass requires destructive field surveys, which is not encouraged for the already rapidly disappearing mangroves, the equations are usually borrowed from other studies. However, studies have shown that the allometric equations vary with species and locations (Komiyama et al., 2008; Yuen et al., 2016). Therefore, we call for the mangrove research community to enlarge the pool of publicly available standardized ground truth datasets.

4.5. Health conditions

Mangrove health analysis, compared to other mangrove problems, is relatively less conducted using RS. We consider that mangrove health research may be further developed in the following two aspects.

(1) LiDAR-based health analysis

Previous studies are mostly based on multispectral or hyperspectral imagery (Song et al., 2011; Wang and Sousa, 2009). Laser-induced fluorescence (LIF) LiDAR, the effectiveness of which on vegetation monitoring has been confirmed two decades ago, can provide another efficient tool for mangrove health analysis through leaf chlorophyll concentration estimation (Günther et al., 1994; Lavrov et al., 2012; Saito et al., 2000; Saito et al., 1997). In addition, with the ability to accurately estimate the chlorophyll concentration, LIF-LiDAR can be used in field survey to provide more detailed validation data for mangrove health status monitoring (Saito et al., 2002).

(2) Red-edge reflectance from satellite images.

Many of the vegetation indices for mangrove health analysis use reflectance around 700 nm, which are usually available from hyperspectral datasets (Wang and Sousa, 2009). However, hyperspectral datasets are often lacked and not easy to collect for large areas. The recently launched Sentinel-2 satellite carry multi-spectral sensors that collect reflectance data at three red-edge bands (705 nm, 740 nm, and 780 nm), which provide essential information for mangrove health analysis (Clevers and Gitelson, 2013; Fernández-Manso et al., 2016; Muhsoni et al., 2018). With its 20 m spatial resolution and 5-day revisit frequency, utilizing Sentinel-2 images will facilitate the timely large-scale monitoring of mangrove health.

4.6. Carbon flux and ecohydrology

Carbon and ecohydrology flux are important for understanding the ecosystem process of mangrove forests. RS has proved to be an effective tool for estimating carbon flux and ecohydrology (Lagomasino et al., 2015b). However, compared to other ecosystems, RS based carbon flux and ecohydrology studies in mangrove forests were rarely conducted. There are two major obstacles: (1) difficulties in acquiring the ecosystem flux data, and (2) difficulties in field survey. In our opinion, recent progress in RS and in-situ instrument may offer two great opportunities in carbon flux and ecohydrology.

(1) Satellite drives large scale carbon flux estimation.

Now, global carbon emissions are monitored from space, by three pioneering satellites: NASA's Orbiting Carbon Observatory-2 (OCO-2), which was launched in 2014 and measures CO_2, Japan's Greenhouse Gases Observing Satellite (GOSAT), which was launched in 2009 and observes CO_2 and methane, and China's TanSat, which was launched in 2016 and examines carbon sources with extremely high precision. Scientists are still trying to figure out how to track greenhouse gases from space (Tollefson, 2016). Meanwhile, a new series of satellites have been lined up to support a larger monitoring effort. Japan launched GOSAT-2 in 2018. NASA is preparing OCO-3 for launch in April 2019. All these satellites could serve as main data sources of global mangrove carbon flux estimation.

(2) In-situ flux tower drives high precision local Carbon flux and ecohydrology estimation.

To our knowledge, except one mobile flux platform study, all RS-based mangrove carbon flux and ecohydrology studies were conducted in Everglade state park, where there is a carbon flux tower. Recently, more and more mangrove carbon flux towers are built worldwide, such as Sundarbans (India), Zhangjiangkou (China), Zhanjiang (China), etc. These towers could serve as high precision data source in local carbon estimations.

4.7. New topics

Significant advances in the field of RS of mangroves were identified in the benefit of the development of earth observation capacity. While recent advances have used some new RS data for existing mangrove research topics, there remain opportunities to explore new topics.

One new topic in RS-based mangrove forests research that we suggest is to map mangrove productivity. Mangrove forests have been considered to be high productivity ecosystem for a long time. However, compared to other ecosystems, less studies focused on mangrove productivity. Moreover, no RS-based researches has been conducted to map mangrove productivity. Nowadays, with intensive mangrove in-situ surveys (Yang et al., 2018) and more flux towers, great opportunities have been offered to the research of mangrove productivity mapping.

5. Conclusion

In this review article, we identified key milestones in mangrove RS by associating emergence of major research topics with occurrence of new sensors in four respective historical phases, i.e. before 1989, 1990–1999, 2000–2009, and 2010-2018. For each identified research topic, an in-depth theoretical understanding was achieved by analyses of both the first published article and most-cited article. Based on the analyses, current state of knowledge as well as existing limitations was summarized. In addition, in order to gain insights on driving forces for emergence of new research topics, we compared the chronological evolution of mangrove RS with that of terrestrial forest RS.

Interestingly, we found out that key research topics in mangrove RS repeats those of forest RS yet with varying time lags. This can be attributed to the following two facts: 1) mangrove forests often appear as more elongated patches than terrestrial forests; 2) field work is more challenging in mangrove habitat. Along with the remote sensors' advancement, various topics that had been studied in terrestrial RS were later transformed to mangrove studies. Based on the projected growth of foreseeing earth observation capacity, insights on future research directions in mangrove RS are also presented.

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