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Challenges and Accomplishments in the Temporal Monitoring of Mangrove Forests Using Remote Sensing Techniques

Monitoring the biophysical properties of mangrove forests from aerial data and images has been a formidable challenge for earth scientists in the past. Remote sensing is an important tool in recording the biomass, species, and carbon stocks of mangrove forests (Pham *et al.* 2019). Mangrove forest monitoring used to only be considered functional at the local level in the nineteen-nineties, whereas permanent monitoring at a regional or global level wasn't yet fathomable (Blasco *et al.* 1998). Fortunately, we now have accurate global distribution and status estimates of mangrove forests around the world (Giri *et al.* 2010). However, temporal studies to monitor essential areas, like the Sundarbans, are continually in need of improvement and updating for the best foresight in saving these biodiverse ecosystems.

Mangroves typically inhabit harsh environments, such as areas with high temperatures, extreme tides, and high salinity, as well as more drastic natural occurrences. Relative sea level rise is one of the most ominous threats to mangrove forests (Giri *et al.* 2011). Mangroves are located in between the land and the sea, in what is known as the intertidal region. This natural positioning of the forests helps protect thousands of families living near volatile coastlines. They also provide nurseries for marine and pelagic species. It has been posited that, although the forests only cover 0.1 percent of the earth's surface, mangroves sequester around 22.8 million metric tons of carbon each year (Giri *et al.* 2011)! The preservation of mangrove forests should be at the forefront of global conservation efforts because of their myriad benefits to humans, endangered animals, and the earth at large.

Figure 1: A map referenced from the World Mangrove Atlas (Spalding *et al.* 1997) displaying the distribution of mangroves in the Indian subcontinent, where mangrove forests are depicted in purple. The Sundarbans, located on the top right of this figure, is the world's largest mangrove forest (Blasco *et al*. 1998).

To create a precise global map of mangrove forests of the world at 30-m resolution, researchers from the second article cited used Global Land Survey (GLS) data from 2000 supplemented by Landsat imagery available from the US Geological Survey (USGS) (Giri *et al.* 2011). They used a hybrid of supervised and unsupervised techniques for digital image classification because of the one thousand Landsat images that needed to be interpreted. Supervised classification is where an analyst selects pixels for the software to base certain classification algorithms, and unsupervised classification is when the software classifies the images without prior alterations. Water bodies were mapped with a supervised classification method because the forests lie in the inter-tidal region, which required human identification methods for quality classification (Giri *et al.* 2010).

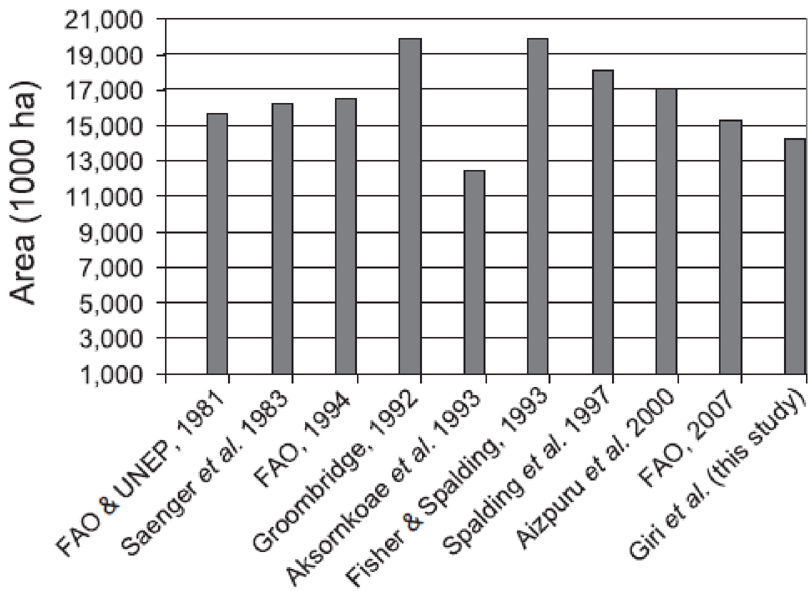

Figure 1: A representative histogram demonstrating the disparity of estimated global mangrove area across multiple studies. The chart primarily illuminates the level of human error in aerial, global estimates of mangrove forests at the time (Giri *et al*. 2010).

High-resolution QuickBird and IKONOS imagery helped the researchers identify and label mangroves while referencing their field data. The researchers did indeed improve upon the global estimate of mangrove forests in 2000 compared to other studies published around the same time. The results estimated that there were 137,760km squared of mangrove forests in 118 countries and territories in 2000. Therefore, the total mangrove area would account for only 0.7 percent of total tropical forests in the world. Asia was found to have a significant majority (42%) of global mangrove biomass relative to the other continents and regions considered (Giri et al., 2010).

The first article cited illuminates the advancements in the usage of remote sensing applications in previously published mangrove studies. Most of the studies analyzed implemented SPOT data and Landsat Thematic Mapper (TM) data. SPOT satellites provide imagery in panchromatic and multispectral bands with a swath of 60 km. TM4 and TM5 were of significance for evaluating the impacts on mangrove soils and tidal penetration on the mean reflectance of mangrove communities. It was mentioned that in the mid-nineteen-nineties, the mapping of mangroves had been extensively developed on all continents due to these data sets (Blasco *et al.* 1998). I agree with the researchers that combining the data sets generated from the ground survey, high-resolution satellite data, and aerial photographs will generate more accurate estimations of mangrove conditions than only using Landsat TM and SPOT data would.

The first and last articles of this paper both illuminate the difficulties of analyzing mangrove species from aerial data with the application of remote sensing techniques. Reflectance spectra of the species can be arduous to decipher because the species are typically intertwined with each other. Furthermore, species located in the same region often display similar reflectance spectra when tested individually. A previous study done on the mangroves of Brazil illuminated how the species show an increase in reflectance around 650 nanometers in almost all parameters (Blasco *et al.* 1998).

No standard method or predetermined recipe for satellite data processing exists that could be applied to any mangrove in the world (Blasco *et al*. 1998). The last article supports this claim because it describes and illustrates how many remote sensing approaches have successfully been implemented in mangrove studies across the globe. The leaf area index (LAI) is considered a vital biophysical parameter in understanding the current condition of mangroves. Recent studies measuring LAI used many different sensors, including LiDAR, WorldView-2, Sentinel-2, Landsat TM, and ALOS AVNIR-2. The paper righteously emphasizes the importance and demonstrates the tactics behind recording above ground biomass (AGB) of mangroves for the mitigation of adverse anthropogenic emissions (Pham *et al.* 2019). I agree with the researchers that machine learning approaches are more effective for estimating mangrove biophysical parameters compared to parametric studies.

Remote sensing approaches have greatly aided in overcoming these aerial mapping obstacles in monitoring mangrove forests or have at least led to further insights into implementing the technology. The references cited demonstrate that remote sensing is a valid and important tool with which to monitor mangroves and their structure. Very high spatial resolution data fortunately provides insights into classifying mangrove species and AGB at multiple spatial scales. However, very high spatial resolution data sets require significant amounts of storage along with other drawbacks (Pham *et al.* 2019). A previous study demonstrated the potential use of normalized difference vegetation index (NDVI) pixel-based for mapping mangrove species in Mexico using different remote sensing data sources from medium to very high spatial resolution. The study concluded that the higher remote sensing data sources were more accurate (Pham *et al.* 2019). The fact that we can now accurately calculate regional and global estimates of mangrove forest biomass from aerial images with the help of remote sensing approaches generates an optimistic outlook for conservation projects ahead.

Bibliography

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