MAPBIOMAS
COLOMBIA

Aprendix - Mangroves

Collection 4

Version 1

Responsible Team:
Karen Andrea Huertas
Julio César Ramírez Yate
Cristian Camilo Durán Corredor

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1. Introduction

Mangroves are highly important coastal ecosystems that provide various cultural, provisioning, regulating, and supporting ecosystem services (Carvajal-Oses et al., 2019; Marlianingrum et al., 2019). Among these services, carbon sequestration stands out, as mangroves can capture up to four times more carbon than other terrestrial forest covers (Spalding & Leal, 2021). In addition, mangroves are known as the "nurseries" of many fish, mollusk, amphibian, and bird species, as they provide shelter, feeding grounds, and spawning or nesting areas (Dirección general de ecosistemas, 2002). Additionally, they play a crucial role as barriers against marine erosion, stabilizing coastlines and protecting coastal communities from strong wave action.

Despite their importance, a significant decline in their global extent has been reported. According to Duke et al.,(2007) mangrove losses over the last quarter-century have consistently ranged from 35% to 86%, with a global annual loss rate of 1% to 2%. However, more optimistic findings have been reported by other authors in recent years, indicating a reduction in global loss rates resulting from improved monitoring and data accessibility, changes in industrial practices, enhanced management and protection, the inaccessibility of the remaining intact mangrove forests, increased implementation of community-based management, a greater focus on rehabilitation, and increased recognition of the ecosystem services provided by mangroves (Friess et al., 2020).

In Colombia, mangroves are found along the Caribbean and Pacific coasts, as well as in the insular territories. In many cases, they are subjected to high levels of disturbance caused by pressures associated with the development of road, tourism, urban, and industrial infrastructure, the intensive exploitation of hydrobiological and timber resources, and land-use change driven by the expansion of the agricultural frontier (Uribe Pérez & Urrego Giraldo, 2009), which not only results in the loss of extensive areas of mangrove cover but also in the release of large amounts of carbon (C) into the atmosphere or ocean (Blanco-Libreros et al., 2015). In this context, as mangrove areas become smaller or more fragmented, their long-term survival is increasingly at risk, and essential ecosystem services may be lost, thereby turning mangroves into a source that contributes to global and regional change.

To establish effective management measures, mapping and monitoring mangrove losses and gains over time are essential. In this regard, Global Mangrove Watch (GMW) is one of the platforms dedicated to providing geospatial information on the global extent of mangroves and the changes observed since 1996 through remote sensing, although not on a continuous basis. At the national level, this work is carried out by the Marine and Coastal Research Institute (INVEMAR) through the SIGMA project.

This document describes the methodological process applied to map mangroves across the Colombian territory as part of MapBiomas Colombia Collection 4.0, which consists of a series of annual land cover and land use maps spanning 1985 to 2025. The methodology is based on that developed by MapBiomas Brazil in previous collections, specifically for mangrove cover. Adjustments and adaptations were made to replicate the method, defining specific work areas and using national reference maps for comparison and validation of the results.

2. Methodological Workflow

The entire process was divided into five main stages: (I) satellite mosaic processing, (II) pre-classification based on satellite mosaics and stable pixels, (III) classification using stable and unstable samples, (IV) application of post-classification filters, and finally (V) integration and validation. In turn, each stage comprised several steps, including the collection of reference data, definition of sampling areas, and preliminary test classifications. A summary of the workflow is presented in Figure 1.

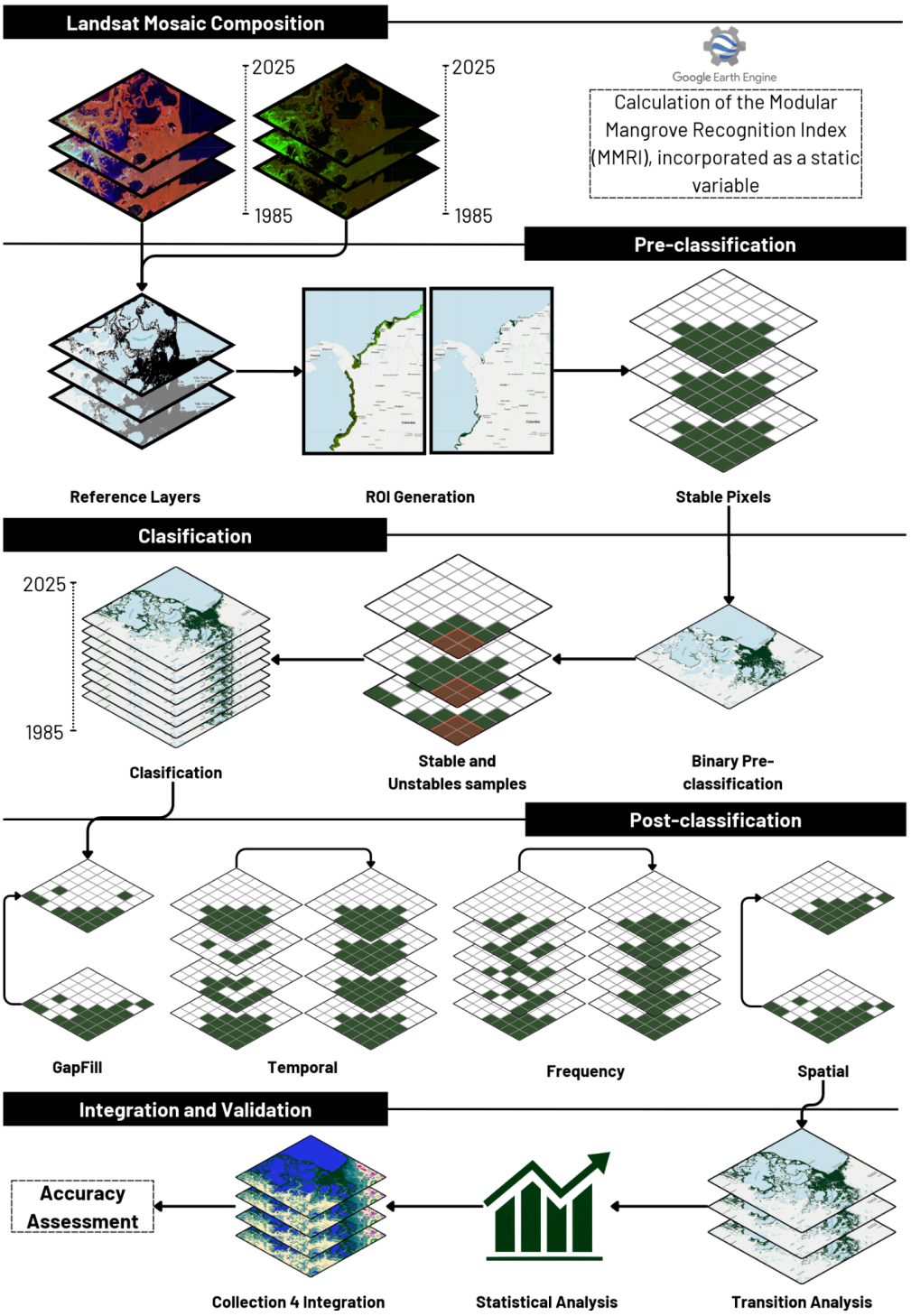
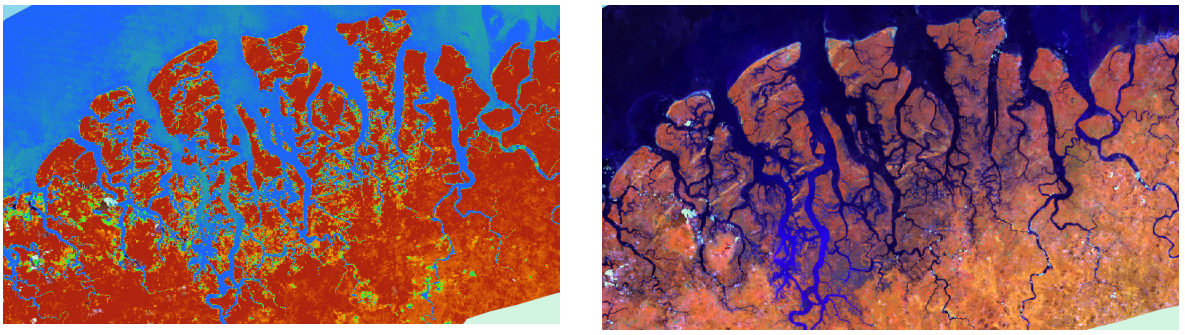


Figure 1. Methodological workflow for the classification of the Mangroves cross-cutting theme in MapBiomas Collection 4.

In previous collections, mosaics based on top-of-atmosphere (TOA) reflectance were used for mangrove detection. These mosaics are generated from orthorectified scenes with the aim of preserving as much of the land surface along coastlines as possible while reducing cloud interference. Additionally, they allow for better calibration of the Modular Mangrove Recognition Index (MMRI). These mosaics use radiometric rescaling coefficients to produce annual cloud-free mosaics (Diniz et al., 2019), thereby significantly improving data integrity by identifying pixels that may be affected by the albedo associated with cloud presence (Chander et al., 2009).

However, difficulties arose in mapping this class, particularly in the Pacific region, due to high rainfall and confusion with flooded forests. Consequently, the methodology was adjusted by using Landsat Collection 4 Surface Reflectance mosaics, available in the Google Earth Engine data catalog. From the total set of available variables, those considered most representative for distinguishing mangrove cover from other classes within the mask were selected, including Landsat bands, spectral indices, and topographic variables, using median and 25th percentile reducers, to train the Random Forest classifier.



Landsat Mosaic
Collection 2 calibrated top-of-atmosphere (TOA) reflectance

Landsat Mosaic
Collection 2 atmospherically corrected surface reflectance

Figure 2. Comparison of the mosaics used for mangrove detection.
TOA mosaics used in Collection 2 and Surface Reflectance mosaics used in MapBiomas Colombia Collection 4

3. Landsat Mosaic Composition

3.1. Landsat Imagery

The mosaics used as the primary input for the mangrove cross-cutting classification were generated from satellite surface reflectance imagery that had undergone atmospheric correction. These images correspond to the Landsat 5, 7, 8, and 9 sensors (Table 1), which cover the area of interest. For each year in the 41-year time series, from 1985 to 2025, a single mosaic was generated using the median pixel reducer at a spatial resolution of 30 meters.

In summary, the script uses the Quality Assessment (QA) band and the GEE median reducer. During processing, the median value of the pixels in each band across the image collection is calculated over the temporal window, rejecting extreme values associated with clouds or shadows (Diniz et al., 2019).

Sensor	ID Colección en GEE
Landsat 4 TM	LANDSAT/LT04/C02/T1_SR
Landsat 5 TM	LANDSAT/LT05/C02/T1_SR
Landsat 7 ETM+	LANDSAT/LE07/C02/T1_SR
Landsat 8 OLI /TIRS	LANDSAT/LC08/C02/T1_SR
Landsat 9 OLI 2 /TIRS 2	LANDSAT/LC09/C02/T1_SR

Table 1. Colecciones de datos Landsat utilizadas en la Colección 4.0.

The annual mosaics generated comprise a set of variables that includes not only the satellite bands but also derived spectral indices, which use the following aggregation methods[1]:

- Median (_median): The pixel value that divides the upper half of the pixel values from the lower half of the dataset. These images correspond to the optimal mapping period defined for each year.
- Dry-season median (_dry): The pixel value that divides the upper half of the pixel values from the lower half of the dataset. These images correspond to the annual 25th percentile of NDVI.
- Wet-season median (_wet): The pixel value that divides the upper half of the pixel values from the lower half of the dataset. These images correspond to the annual 75th percentile of NDVI.
- Amplitude (_amp): Difference between the two extremes of the annual pixel value range.
- Standard deviation (_stdDev): A measure of dispersion calculated as the square root of the variance of the annual pixel values.
- Minimum (_min): The lowest pixel value within the dataset.
- Maximum (_max): The highest pixel value within the dataset.

[1] These aggregation methods were applied to the Landsat images selected by path/row and to all spectral indices derived from them.

The selection of scenes and generation of the final mosaics were carried out using the parameters listed below as a reference, which were stored as metadata in each asset created:

- ID: Unique identifier for the region .
- Year: Year in the time series (1985–2025) to which the mosaic corresponds.
- Start and end dates: Period of the year (start and end dates) used to select images from the Google Earth Engine Landsat imagery data catalog.
- - Sensor: Satellite and corresponding sensor: Landsat 4 TM, Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, Landsat 9, or combinations of Landsat 5 and Landsat 7 (LX), and Landsat 8 and Landsat 9 (LY).
- Cloud cover: Maximum allowable cloud cover percentage. Landsat scenes exceeding this threshold are excluded from the median mosaic generation.
- Blacklist: List of scenes excluded from mosaic generation due to their quality.

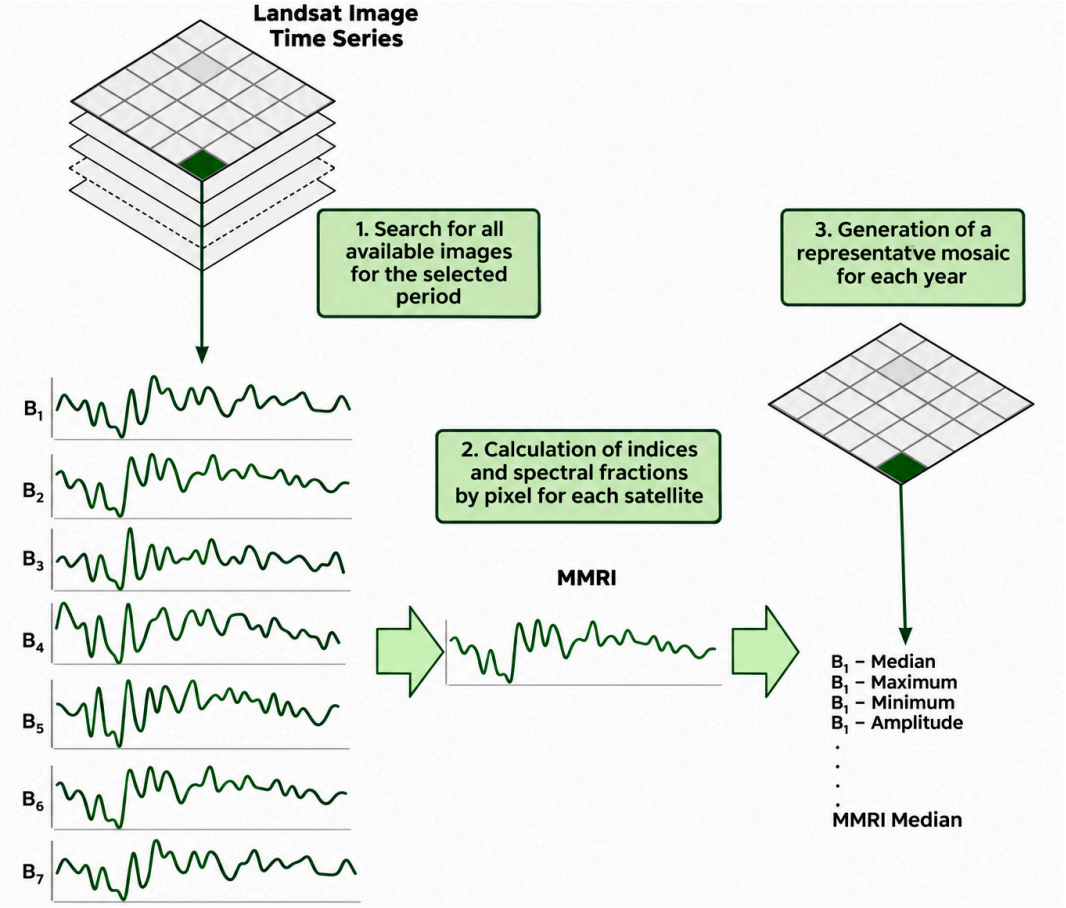


Figure 3. Method for generating annual mosaics and calculating spectral indices for MapBiomas Colombia Collection 4.0.

Among the spectral indices calculated from the extracted spectral attributes (see Figure 3), the most relevant is the Modular Mangrove Recognition Index (MMRI). This index is incorporated as a static variable and is based on the combination of two conventional indices: the Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI). The corresponding equation is presented below:

$$MMRI = \frac{|MNDWI| - |NDVI|}{|MNDWI| + |NDVI|}$$

3.1.1. Topographic Correction

In this collection, an improvement has been implemented through the application of topographic correction to the Landsat mosaics used. This correction significantly reduces the impact of terrain shadows in areas with steep slopes and contributes to the homogenization of mapping areas. It is important to note that illumination conditions, determined by the sensor's zenith angle at the time of image acquisition, affect light reflectance values. This optimization results in a more uniform and reliable representation of the landscape.

3.2. Classification Variable Selection

Preliminary classification tests were conducted using the generated mosaics to identify the most relevant variables. Based on these results, three topographic variables derived from the SRTM digital elevation model (elevation, slope, and slppost) were included, bringing the total to 14 variables (Table 2).

Band	Description	Reductor
green	Green band value	Median
red	Red band value	Median
nir	Near-infrared (NIR) band value	Median
swir1	SWIR1 band value	Median
swir2	SWIR2 band value	Median
BQA	Quality Assessment (QA) band value	
CAI	Cellulose Absorption Index	Median
EVI	Enhanced Vegetation Index	Median
GCVI	Green Chlorophyll Vegetation Index	Median
NDFI	Normalized Difference Fraction Index	Median
NDVI	Normalized Difference Vegetation Index	Median
SAVI	Soil-Adjusted Vegetation Index	
NDWI	Normalized Difference Water Index	
MNDWI	Modified Normalized Difference Water Index	
NDSI	Normalized Difference Soil Index	
MMRI	Modular Mangrove Recognition Index	
slope	Slope	
slppost	Stratified slope	
altitude	Elevation	

Table 2. Variables for Mangrove Classification in MapBiomas Colombia Collection 4.0.

4. Classification

4.1. Class Definition

Mangroves (ID 5) are natural formations of dense, evergreen forests located in coastal areas, occupying a transitional zone between the mainland and the ocean (García Murcia & Cortes Castillo, 2018). They develop on sandy or silty clay soils that may be permanently or occasionally inundated by tidal action. They form belts along estuaries, bays, coves, coastal lagoons, river mouths, tidal channels, and other areas where they receive freshwater inputs from continental runoff and are influenced by marine or brackish waters (Díaz Gaxiola, 2011).

Due to climatic and soil conditions, as well as oceanographic and fluvial factors, mangrove vegetation exhibits distinctive morphological and physiological characteristics that enable it to grow in unstable, anaerobic, and flood-prone environments, where soils have low oxygen concentrations and high salinity. These adaptations include elongated, flexible roots that allow colonization of unstable substrates, anatomical structures known as lenticels and pneumatophores that facilitate gas exchange with the atmosphere, and reproductive strategies such as seeds that can remain afloat for extended periods of time (Villalba Malaver, 2006). In Colombia, mangroves are found along the Pacific and Caribbean coasts.

4.1.1. Caribbean Mangrove

In the Caribbean region, mangroves reach heights of 3 to 20 m, which are lower than those found along the Pacific coast. They are distributed from the Gulf of Urabá (Antioquia) to Turkakas Bay in the Upper Guajira, occurring at the mouths of major rivers such as the Atrato, Sinú, and Magdalena, as well as along the shores of coastal wetlands, in Tayrona National Natural Park, in Camarones, and in the Ranchería River delta in La Guajira. Mangroves are also found in insular areas, particularly in the San Andrés and Providencia Archipelago. Their floristic composition in the Caribbean includes five genera: *Rhizophora*, *Avicennia*, *Laguncularia*, *Pelliciera*, *and Conocarpus* (Villalba Malaver, 2006).

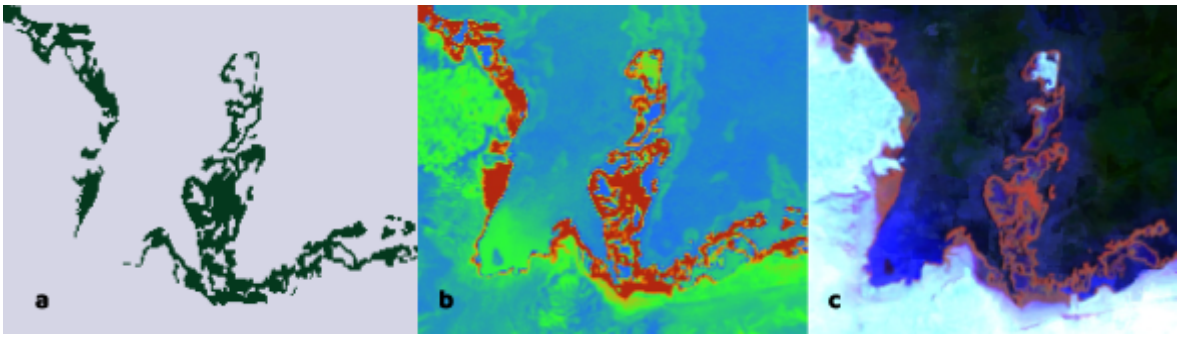




Figure 4. Reference images for the Caribbean Mangrove class.
(a) Land Cover Classification
(Legend: Mangrove, No mangrove zone); (b) MMRI Mosaic; (c) Landsat Mosaic (RGB); (d) Google Street View Image (-71.96417 , 12.1602)

4.1.2. Pacific Mangrove

Mangroves along the Colombian Pacific coast reach heights of up to 40 m and exhibit greater species diversity. They extend along the coastline and into some river deltas that reach inland, from Utría Cove and Nuquí to the mouths of the Baudó and San Juan rivers. Further south, they are found again in Málaga and Buenaventura bays, extending as far as Tumaco, near the border with Ecuador (Villalba Malaver, 2006).

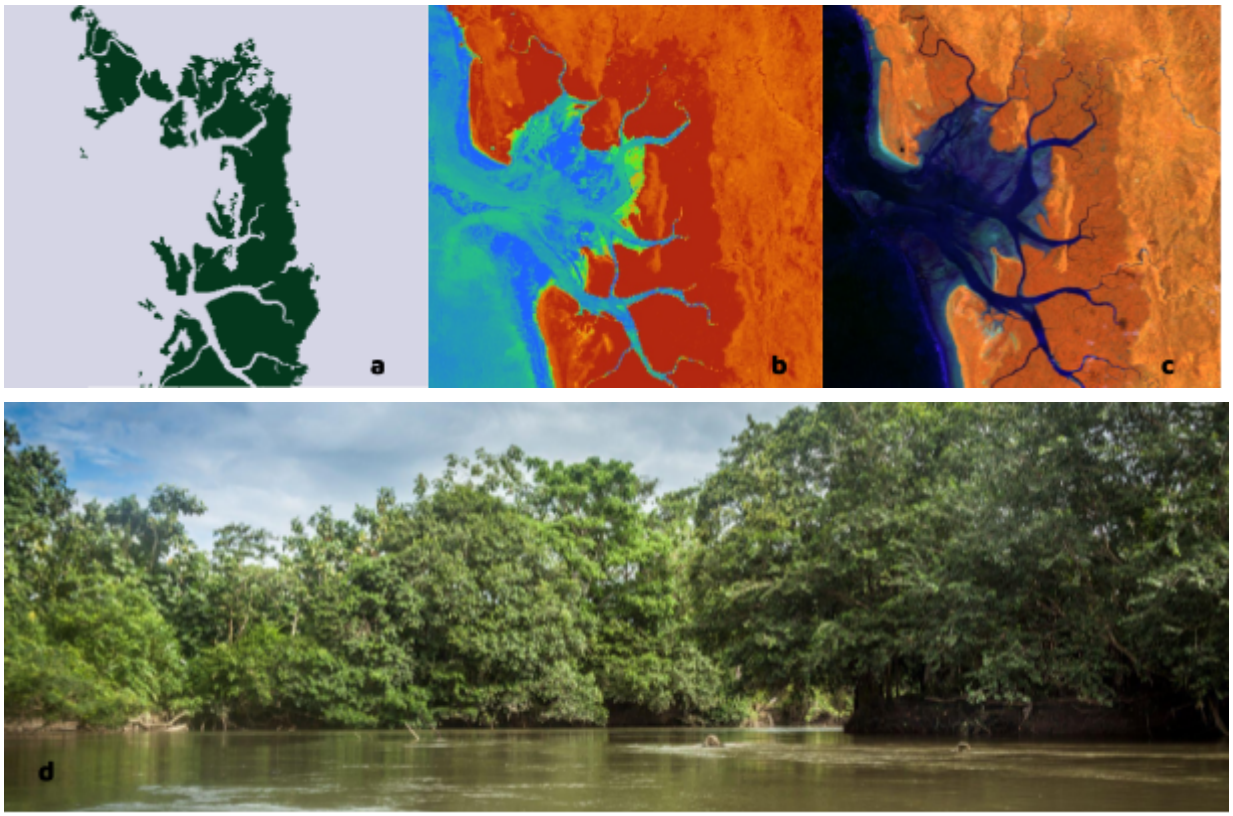


Figure 5. Reference images for the Pacific Mangrove class
(a) Clasificación de cobertura
(Legend: Mangrove, No mangrove zone); (b) MMRI Mosaic; (c) Landsat Mosaic (RGB); (d) Image of Pacific mangroves (WWF, s. f.)

4.2. Classification Regions

Based on the Landsat mosaics generated, a supervised classification was performed using the Random Forest algorithm. All processing was carried out on the Google Earth Engine platform, and the results were stored as an image collection within the platform. Land cover detection focused on identifying the mangrove class (ID 5 in the MapBiomas Colombia Collection 4.0 legend) in the Caribbean and Pacific biogeographic regions. The classification process considered only two possible classes: the target class (mangroves) and the Unobserved class (all land cover types other than mangroves).

To facilitate the classification process, "classification regions" were delineated based on geographic and topographic criteria, as well as land cover continuity. As a result, nine classification regions were defined, as shown in Figure 6: four in the Caribbean region, four in the Pacific region, and one in the insular Caribbean. These regions are numbered from 30401 to 30409.

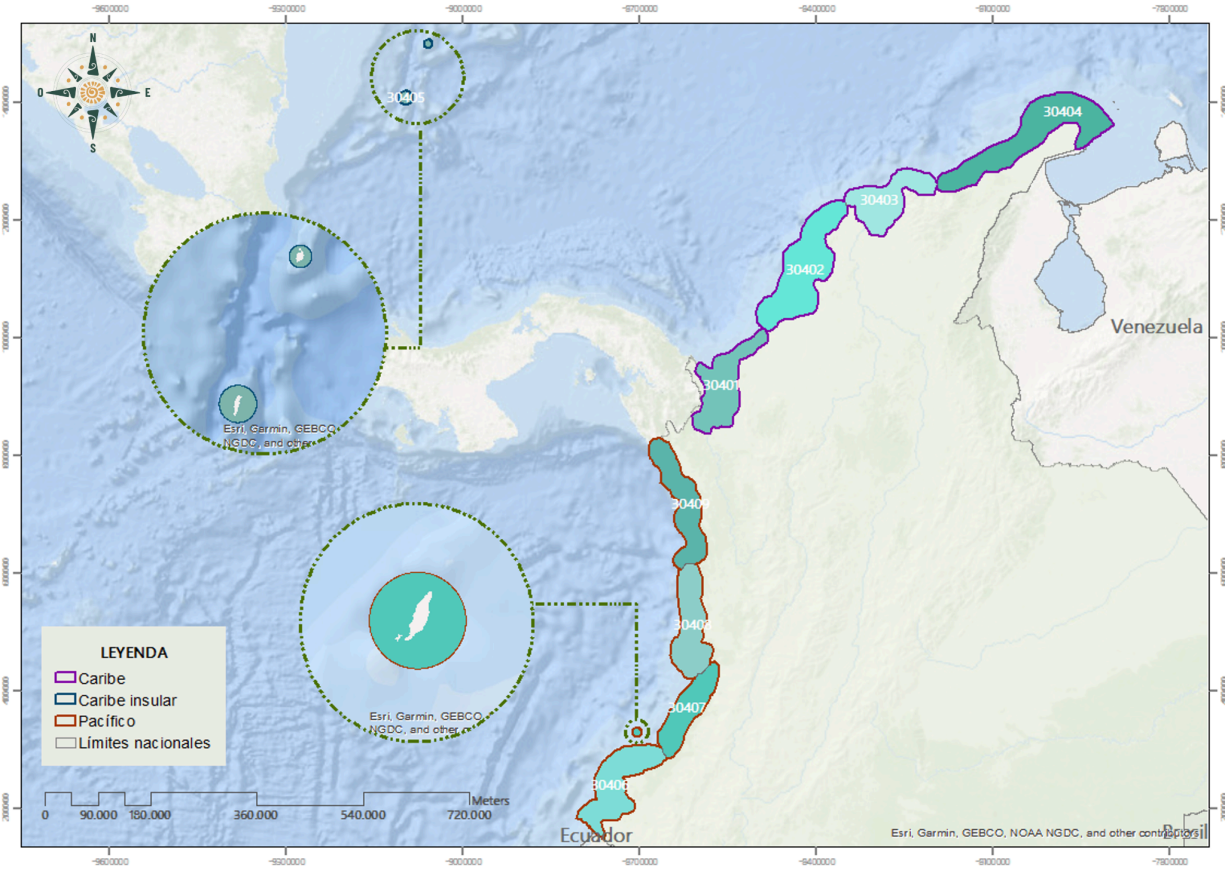


Figure 6. Classification regions and working mask for the Mangroves cross-cutting theme in MapBiomas Colombia Collection 4.0.

4.3. Reference Information

The training samples used for classification were generated within the area of overlap between the mangrove reference layers, defining a region of interest (ROI) or working mask (Table 3). Additionally, stable samples of the class were included, corresponding to pixels classified as mangrove in every year of the Collection 4 time series (1985–2025), as well as in the cumulative layer covering the entire time period. These results were incorporated as an additional layer.

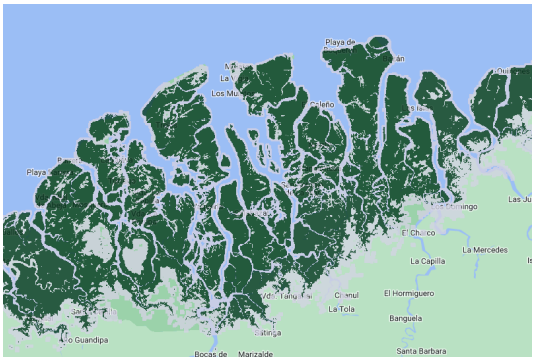
Reference	Global	Colombia
Global Mangrove Watch (GMW)	x	x
Global Mangrove Forests Distribution	x	x
Global Mangrove Distribution (USGS)	x	x
IDEAM 2017		x
CLC 2018		x
National reference		x
Stables points Collection 4 MapBiomas		x
Colección 4 MaBiomas accumulate		x

Table 3. Reference layers for the Mangrove class.

4.4. Training Samples

Once all reference layers for the country had been merged, training samples were randomly selected for the mangrove class (ID 5) and the Unobserved class (ID 27), which grouped all land cover types other than mangroves. Additionally, a function was implemented to exclude or select sampling areas based on geometries, thereby preventing errors arising from inconsistencies in the reference layers.

(a)



(b)

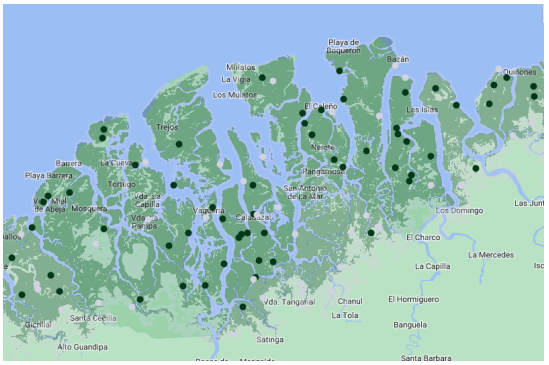


Figure 7. Training Samples.
Image (b) shows the randomly selected points for the mangrove (dark green) and non-mangrove (gray) classes, based on the mask generated from the intersection of the reference layers (a).

5. Post-classification

Due to the use of a pixel-based classification approach over an extensive 41-year time series, mapping inconsistencies are common, including noise, salt-and-pepper effects, data gaps, and temporal inconsistencies. Therefore, a series of post-classification filters was applied iteratively: gap-filling, temporal, spatial, and frequency filters.

5.1. Gap-Fill Filter – Filling Data Gaps

The filtering sequence begins with filling data gaps. In some years, the sensor's default mosaic may be partially or entirely unavailable. Additionally, some regions, particularly the Pacific region, are severely affected by cloud cover, which may result in gaps in the median composite. This filter replaces pixels with no data using the classification from the temporally closest available year (Figure 8). If no value is available for the immediately preceding year, the gap is filled using the value from the following year. Thus, remaining gaps should only occur when a given pixel has been consistently classified as having no data throughout the entire time series.

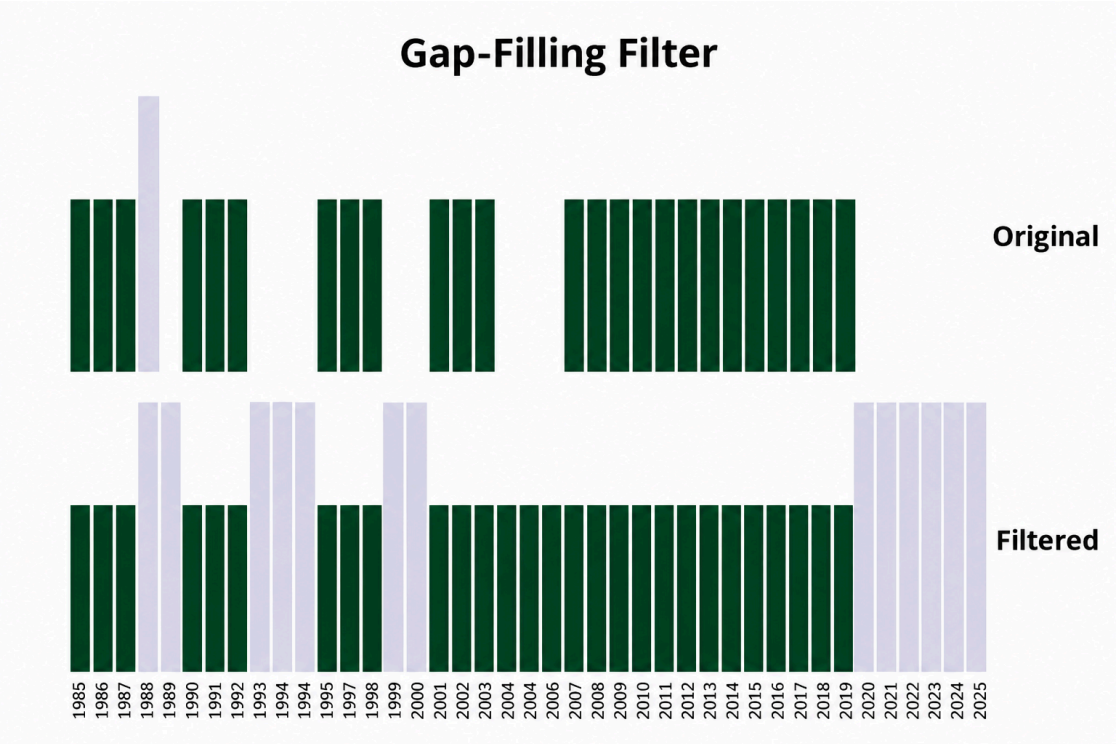


Figure 8. Example illustrating the operation of the gap-filling filter.

5.2. Temporal Filter

The temporal filter uses sequential classifications within a unidirectional moving window of 3, 4, or 5 years across the entire time series. Its purpose is to identify temporally impermissible transitions, that is, abrupt changes that are inconsistent with the behavior of the mapped land cover. The temporal filter is applied according to three rules:

- First-Year Rule (FYR): Applied only to the classification of the first year of the time series (1985), where an abrupt change from the temporal continuity of the series is identified.
- Last-Year Rule (LYR): Applied only to the classification of the last year of the time series (2025), where an abrupt change relative to previous years is identified.



Figure 9. Example illustrating the operation of the gap-filling filter.

- General Rule or Intermediate-Year Rule (GR): Applied to all intermediate years of the time series (1986–2024), replacing pixel values in the intermediate position where a temporal inconsistency occurs with the value of the corresponding endpoint. In 3-year sequences, there is only one possible central position or intermediate year, whereas 4- or 5-year sequences offer two or three possible central positions, as shown in Figure 9.

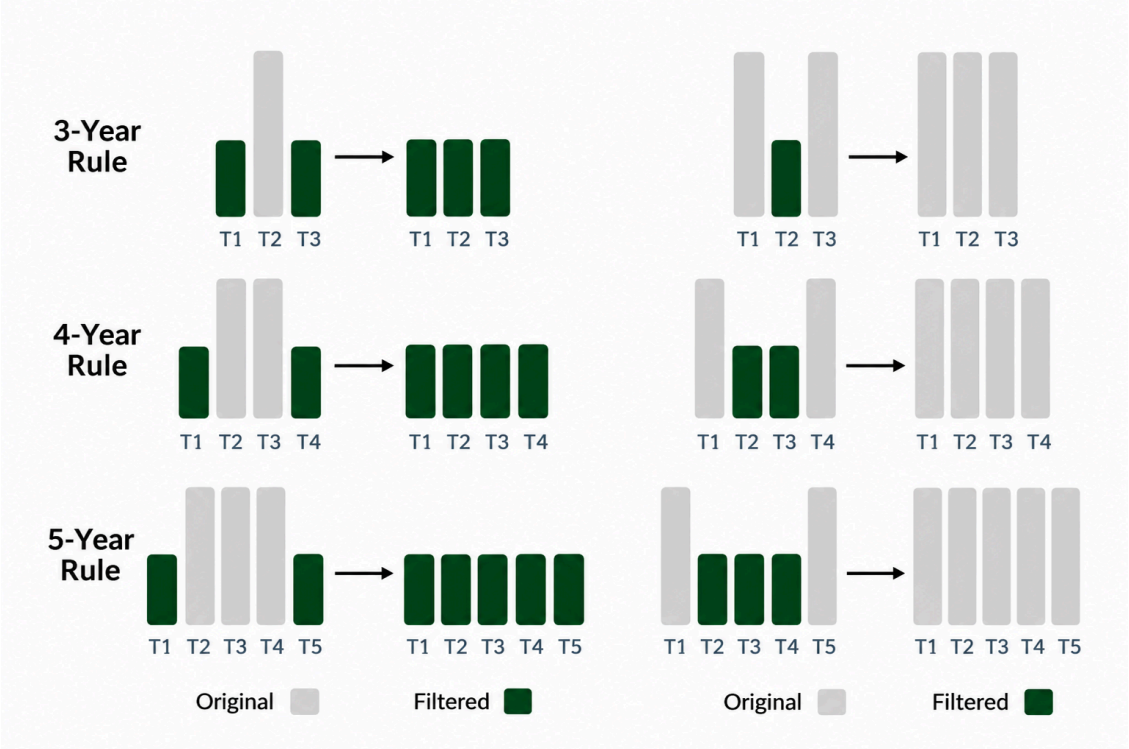


Figure 10. Example illustrating the operation of the temporal filter.

5.3. Spatial Filter

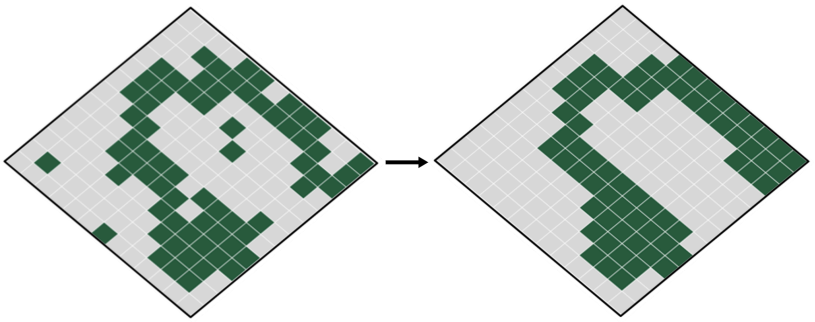


Figure 11. Effect of applying the spatial filter.

The spatial filter is based on the connectedPixelCount function, which homogenizes the classification by assigning isolated pixels the value of the class in which they are embedded and/or that predominates in their surroundings. To be considered a representative group of pixels, they must be connected to one another and meet a minimum area threshold of 0.5 hectares, equivalent to 5 pixels. Thus, isolated pixels that do not meet this condition are reclassified, reducing classification noise and consolidating land cover patches within the mosaic. Figure 11 shows an input image (CO) containing an isolated pixel, which, after the filter is applied (CF), is replaced by the predominant surrounding class.

5.4. Frequency Filter

Finally, the fourth filter in the post-classification sequence was the frequency filter. As shown in Figure 12, this filter considers the percentage of occurrence of each class throughout the time series to refine the classification results, assigning each pixel the same land cover class from 1985 to 2025.

This filter was applied differently to class 5 (mangrove) and class 27 (Unobserved), the latter grouping all classes within the classification mask that do not correspond to the cross-cutting theme under consideration. First, the filter made it possible to complete the mangrove cover classifications in areas where omissions caused by the mosaic or errors during the classification process resulted in underestimation that could not be corrected using the temporal filter.

Secondly, the filter helped remove residual noise, which is particularly common in the Colombian Pacific due to the region's high rainfall, resulting in frequent cloud cover in the mosaics. Figure 12 illustrates the effect of this filter.

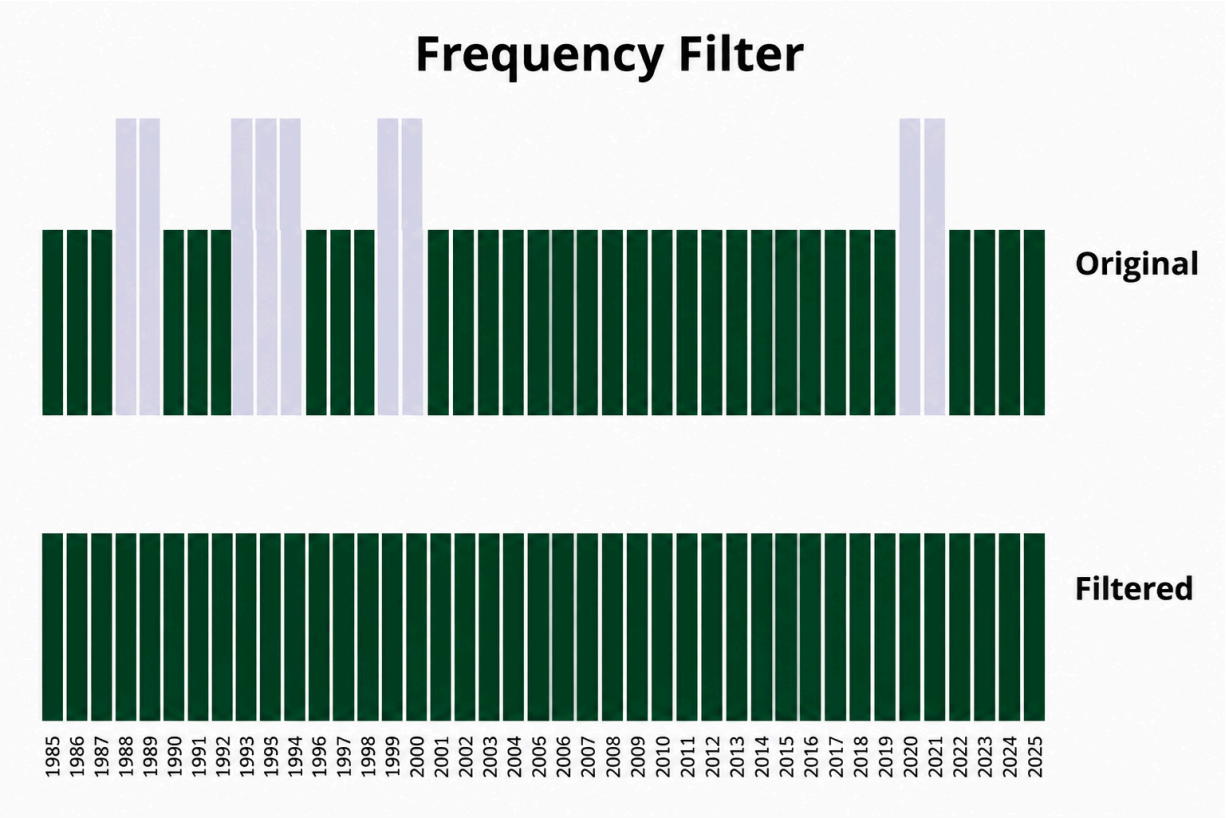


Figure 12. Effect of Applying the Frequency Filter.

6. Integration with Other MapBiomas Colombia Classes

Following the application of the filter sequence during the post-classification stage, the cross-cutting themes and the general maps for each biome are integrated. This integration is governed by a set of specific hierarchical rules that establish the order of precedence for each class. This stage produces the annual land cover and land use maps for the entire Colombian territory. Tables 4 and 5 present the integration order for the Pacific and Caribbean biogeographic regions, respectively, where the mangrove cross-cutting theme was mapped.

Pacific		
Class	ID	Integration order
Rocky outcrop	29	1
Infrastructure	24	2
Mining	30	3
Forest plantation	9	4
Other natural non-vegetated area	68	5
Beach, dune and sand spot	23	6
River, lake or ocean	33	7
Palm oil	35	8

Aquaculture	31	9
Mosaic of agriculture and pasture	21	10
Other non-vegetated area	25	11
Wetland	11	12
Mangrove	5	13
Flooded forest	6	14
Other non forest formation	13	15
Forest formation	3	16

Table 4. Integration Rules for the Pacific Region.

Caribbean		
Class	ID	Integration order
Glacier	34	1
Rocky outcrop	29	2
Mining	30	3
Infrastructure	24	4
Forest plantation	9	5
Palm oil	35	6
Other natural non-vegetated area	68	7
Beach, dune and sand spot	23	8
River, lake or ocean	33	9
Mangrove	5	14
Aquaculture	31	10
Mosaic of agriculture and pasture	21	11
Other non-vegetated area	25	12
Wetland	11	13
Flooded forest	6	15
Other non forest formation	13	16
Forest formation	3	17

Wooded sand vegetation	49	18
Herbaceous sand vegetation	50	19

Table 5. Integration Rules for the Caribbean Region.

7. References

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