



Appendices - Mangrove
Cross-cutting theme - collection 1.0

1. General Description

This document describes the methodology used for the classification and mapping of mangrove ecosystems in Mexico as a cross-cutting theme within MapBiomass Mexico Collection 1. The final map covers the coastal zone where mangroves occur for the period 1985-2025, at a spatial resolution of 30 meters, using Landsat satellite imagery processed on the Google Earth Engine (GEE) platform.

Mexico ranks as the fourth-largest country in the world in terms of mangrove extent, containing approximately 6% of the global mangrove area. Four main mangrove species (*Rhizophora mangle*, *Laguncularia racemosa*, *Avicennia germinans*, and *Conocarpus erectus*) are distributed along the country's coastline, while two additional species (*Rhizophora harrisonii* and *Avicennia bicolor*) have a restricted distribution in the southern Mexican Pacific, specifically in the states of Oaxaca and Chiapas. These ecosystems are protected under the General Wildlife law (Article 60 Ter), the General Law of Ecological Balance and Environmental Protection, and the Mexican Official Standards NOM-022-SEMARNAT and NOM-059-SEMARNAT-2010, which collectively establish the legal framework for mangrove conservation in Mexico. These legal instruments recognize the critical role of mangroves in providing essential ecosystem services, including coastal protection, blue carbon storage, habitat for marine species, and support for fisheries production.

The methodology described here was designed to account for the ecological conditions, spectral characteristics, and phenological behavior of Mexican mangroves. It builds upon the accumulated experience of the Mexico Mangrove Monitoring System (SMMM-CONABIO), while incorporating algorithms and predictor variables developed for MapBiomass Brazil (Collection 9) and MapBiomass Ecuador (Collection 3).

1.1 Differences from the General MapBiomass Mexico Workflow

The mangrove cross-cutting theme operates as an overlay map on top of the general MapBiomass Mexico Collection 1 land cover map. Unlike the general workflow, which classifies 16 land cover classes across five physiographic regions, the mangrove workflow has the following characteristics:

- It operates within nine coastal zones defined by coastal environmental characteristics, rather than continental physiographic regions.
- It classifies six contextual classes (mangrove, other forests, herbaceous and shrub vegetation, agricultural land, non-vegetated areas, and water bodies) instead of the 16 general land cover classes.
- It incorporates specialized spectral indices for mangrove mapping (MMRI, CMRI, LSWI, and MNDWI) derived from the existing Landsat mosaics.
- The training samples are intrinsically stable (land cover that remained unchanged throughout the 41-year period), eliminating the need for the stable sample export step required in the general workflow.
- The final product is a single national mangrove map created by integrating the

classifications from the nine coastal zones and clipping the results to the national boundaries of Mexico.

2. National Coastal Zoning

Because the environmental conditions along the Mexican coastline vary substantially among regions –resulting in distinct spectral responses and phenological patterns of mangrove ecosystems- the national coastline was divided into nine classification zones (Table 1 and Figure 1). This regionalization enables the Random Forest classifier to be trained separately for each environmental context, thereby improving classification performance and reducing spectral confusion among land cover classes.

Table 1. Coastal zoning of Mexico used for mangrove classification

Zone	Name	States
1	Alto Golfo y Centro	Tamaulipas, Veracruz
2	Golfo Sur Oriental	Tabasco, Campeche
3	Norte Península de Yucatán	Campeche (Petenes), Yucatán
4	Mar Caribe Norte	Quintana Roo (norte)
5	Mar Caribe Sur — Sian Ka'an	Quintana Roo (sur)
6	Pacífico Norte	Baja California, BCS, Sonora, Sinaloa
7	Pacífico Marismas Nacionales	Nayarit
8	Pacífico Centro y Sur	Jalisco, Colima, Michoacán, Guerrero, Oaxaca
9	Pacífico Sur — Chiapas	Chiapas



Figure 1. Spatial distribution of the nine coastal classification zones defined to account for regional environmental variability in the mangrove classification workflow.

3. Landsat Imagery and Mosaics

3.1 Data source

The classification was based on the annual Landsat mosaics available through the MapBiomass Mexico platform in the following Google Earth Engine asset: [projects/mapbiomas-mosaics/assets/LANDSAT/LULC/MEXICO/mosaics-1](https://projects.mapbiomas-mosaics/assets/LANDSAT/LULC/MEXICO/mosaics-1)

These mosaics are derived from Landsat 5, 7, and 8 Collection 2 Tier 1 imagery, processed using a median reducer and cloud masking based on the QA band. Each annual mosaic contains 122 bands, including spectral reflectance bands, vegetation indices, water indices, and spectral mixture fractions for three temporal periods: annual, dry season and wet season.

3.2 Temporal Coverage

The time series spans the period 1985-2025, representing 41 years of continuous monitoring. Not all years provide complete coverage across every coastal zone due to the historical availability of Landsat imagery and persistent coastal cloud cover. Years with insufficient image availability are filled using the GapFill filter described in Section 6.

3.3 Derived Spectral Indices

In addition to the spectral bands and indices included in the original mosaics, specialized

indices for mangrove detection were derived. All computed indices were scaled to the uint16 data format (0-65,535) to ensure consistency with the remaining mosaic bands.

Table 2. Spectral indices additionally derived for mangrove classification.

Index	Name	Description	Formula	References
MNDWI	Modified Normalized Difference Water Index	Modified index for improving the detection of water bodies in vegetated areas.	$(\text{Green} - \text{SWIR1}) / (\text{Green} + \text{SWIR1})$	Xu, 2006
MMRI	Modular Mangrove Recognition Index	Index designed to enhance mangrove vegetation by combining the near-infrared and green signals while reducing the influence of the shortwave infrared band.	$(\text{MNDWI} - \text{NDVI}) / (\text{MNDWI} + \text{NDVI})$	Diniz et al., 2019
CMRI	Canopy Mangrove Recognition Index	Improves mangrove identification by using the normalized difference between the near-infrared and red bands.	$\text{NDVI} - \text{MNDWI}$	Duke et al., 1998
LSWI	Land Surface Water Index	Index used to enhance the detection of water and moisture-saturated soils.	$(\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$	Xiao et al., 2004

4. Classification

4.1 Classification Scheme

Unlike MapBiomass Brazil, which performs a binary classification (mangrove vs. non-mangrove), the approach implemented for MapBiomass Mexico uses a multiclass classification scheme with six land cover classes. This approach enables the Random Forest classifier to better distinguish mangroves from the range of land cover types that coexist along the Mexican coastline.

Table 3. Classification scheme used for the mangrove cross-cutting theme.

Code	Class	Description
5	Mangrove	Coastal halophytic Woody vegetation, including <i>Rhizophora mangle</i> , <i>laguncularia racemosa</i> , <i>Avicennia germinans</i> , <i>Rhizophora harrisonii</i> , <i>Avicennia bicolor</i> , and <i>Conocarpus erectus</i> .
1	Other Forests	Non-mangrove coastal tree vegetation, including tropical forests and riparian forests.
2	Herbaceous and Shrub vegetation	Grasslands, cattail marshes, and herbaceous halophytic vegetation.
3	Agricultural Land	Croplands, cultivated pastures, and shrimp aquaculture.
4	Non-Vegetated Areas	Bare soil, beaches, urban areas, and hypersaline mudflats.
55	Water Bodies	Sea, coastal lagoons, rivers, and estuaries.

4.2 Classification Algorithm

The Random Forest classifier (Breiman, 2001), implemented in Google Earth Engine (smileRandomForest) was used with the following parameter:

Table 4. Random Forest classifier parameters.

Parameter	Value
Number of trees	100
Random seed	15
Number of classes	6 (multiclass)
Number of predictor variables	27
Classification scale	30 m

4.3 Predictor variables (input Properties)

A total of 27 predictor variables were selected for the classifier and organized into five functional groups:

Base spectral bands (6 variables)

Annual, dry-season, and wet-season NIR; annual, dry-season and wet-season SWIR1. These spectral bands provide the greatest discriminatory power for separating mangrove from water and bare soil.

Vegetation vigor indices (6 variables)

Annual, dry-season and wet-season NDVI, together with its seasonal amplitude (NDVI_amp); dry-season, and wet-season EVI2. The low seasonal amplitude of NDVI is a characteristic feature of evergreen mangrove forests. Unlike NDVI, EVI2 is less prone to saturation in high-biomass canopies, such as mature mangrove stands.

Interstitial water and vegetation water content indices (6 variables)

Dry-season and wet-season MNDWI (derived); dry-season and wet-season LSWI (derived); and dry-season and wet-season NDWI (from the mosaics). These indices capture water within the mangrove root zone as well as vegetation water content.

Mangrove-specific indices (4 variables)

Dry-season and wet-season MMRI; dry-season and wet-season CMRI. The Modular Mangrove Recognition Index (MMRI) was specifically developed for Brazilian mangroves (Diniz et al., 2019) and has been successfully applied to the Mexican Pacific coast. The Canopy Mangrove Recognition Index (CMRI) improves the discrimination of mangroves from other coastal forest types.

Spectral mixture variables (5 variables)

Dry-season GVS (green vegetation fraction plus shade): dry-season and wet-season NDFI; wet-season WEFI (Water Edge Fraction Index); and dry-season Shade. The dense, closed canopy of mangrove forests typically produces high values of both Shade and GVS.

5. Training Samples

5.1 Sampling Design

Training samples were manually collected through visual interpretation in the Google Earth Engine (GEE) Code Editor using the following datasets as reference:

- Landsat mosaics displayed in a false-color composite (SWIR1-Red-Green) for three reference periods: 1985, approximately 2000, and 2025.
- Mangrove maps from the Mexico Mangrove Monitoring System (SMMM-CONABIO), including the 1970-2020 persistent mangrove map for each coastal zone.
- The MMRI calculated from the Landsat mosaics to identify areas with a high probability of mangrove occurrence.

Training samples were designed as stable polygons, representing land cover that remained unchanged throughout the 41-year time series. This approach eliminates the need for the ExportTrainedStable step used in the general MapBiomass Mexico workflow, since the samples are intrinsically stable by design.

5.2 Spectral Signature Extraction

After the polygons were collected for each coastal zone, spectral signatures were extracted from the Landsat mosaics for every available year using the sampleRegions function with a 30 m spatial resolution. The extraction was performed on the Landsat collection enriched with the derived mangrove-specific indices (MMRI, CMRI, LSWI, and MNDWI).

The resulting samples include the 122 bands from the original mosaics plus the 6 derived bands, yielding a total of 128 variables per sample-year. Only the variables defined in inputProperties (27 predictor variables) were retained for Random Forest training.

5.3 Sample Balancing

To avoid class imbalance between the target class (mangrove), which occupies a relatively small proportion of the study area, and the surrounding land cover classes, an empirical sample balancing procedures was applied for each year.

Table 5. Sample balancing by class and year for Random Forest training

Code	Class	Maximum samples per year
5	Mangrove	50
1	Other Forests	150
2	Herbaceous and Shrub vegetation	150
3	Agricultural Land	150
4	Non-Vegetated Areas	150
55	Water Bodies	150

Mangrove was assigned a lower sampling limit (50 samples) to reduce the overfitting, given the static nature of the sampling polygons. The contextual classes were assigned a higher limit (150 samples) to ensure that the Random Forest classifier adequately learned the decision boundaries between mangrove and non-mangrove classes. Only classes with at least two available samples in the evaluated year were included.

5.4 Stable Map Samples

To enrich the training dataset with spatially distributed samples across the entire coastal zone, additional samples derived from the stable pixel map (section 5.5) were incorporated. These samples improve spatial representativeness in coastal areas where manual digitization did not provide complete coverage.

Stratified sampling on the stable map was performed using the following limits: 200 samples for mangrove and water bodies, and 100 samples for each of the remaining classes. Spectral signatures were extracted for each year within the classification loop using the corresponding annual Landsat mosaic.

5.5 Stable Pixel Map

As an intermediate processing step, stable pixel maps were generated for each coastal zone. These maps identify pixel that were assigned to the same class by the Random Forest classifier in every available year. Pixel stability is determined by counting the number of distinct classes observed throughout the time series: a pixel is considered stable when this number equals one.

Although this step corresponds to Script 3 (ClassifStable) in the general workflow, within the mangrove cross-cutting theme it is used primarily to enrich the training dataset (Section 5.4) and as a visual quality-control tool, rather than as a mandatory processing step.

6. Post-Classification

Because of the pixel-based nature of the classification approach and the length of the time series (41 years), a sequence of three post-classification filters was applied. This filtering chain is equivalent to that used in MapBiomass Brazil Collection 9 (Diniz et al., 2019) and is

executed in the following order.

6.1 GapFill Filter

The first filter fills years with missing classifications. Along the Mexican coastline, some years have insufficient Landsat image coverage –particularly during the 1985-1995 period, when only Landsat 5 was operational- preventing the generation of high-quality mosaics. These years are therefore excluded from the classification loop.

The GapFill operates in two sequential steps. First, it performs a forward fill, replacing missing years with the classification from the most recent previous year available. Second, it performs a backward fill, assigning the earliest missing years in the time series the classification from the nearest subsequent year.

In addition to filling missing values, the GapFill procedure computes the connectedPixelCount for each year-band, which is used as a diagnostic input in subsequent processing steps.

6.2 Temporal Filter

The temporal filter applies as three-year moving window to identify and correct temporally isolated classification changes. The general rule is: if the two outer years of a three-year sequence ($T-1$, T , $T+1$) belong to the same class while the central year differs, the central pixel is reclassified to match its temporal neighbors.

The filter is particularly important for mangrove mapping because it prevents poor-quality imagery or excessive cloud cover in a single year from producing spurious land-cover changes. Water bodies (Class 55) are excluded from the temporal filter because they may legitimately vary between wet and dry years.

The filter is applied sequentially to each of the five terrestrial classes (1, 2, 3, 4, and 5). Since the first and last years of the time series lack both preceding and following observations, they are retained without modification.

6.3 Spatial Filter

The spatial filter removes isolated pixel patches that do not share a sufficient number of neighboring pixels belonging to the same class. It is based on the native Google Earth Engine connectedPixelCount function, which calculates the number of connected pixels of the same class for every pixel.

Pixels with fewer than six connected neighbors (approximately 0.54 ha) are replaced by the 3 x 3 focal mode of their neighborhood. This threshold was selected to avoid removing genuinely small mangrove patches, which are common along the Mexican coastline.

Unlike MapBiomas Brazil Collection 9, which uses a minimum mapping unit of 10 connected pixels (approximately 1 ha), a threshold of 6 connected pixels was adopted to preserve the

integrity of small mangrove patches in Mexico.

7. National Integration and Final Products

7.1 Integration of the Coastal Zones

After post-classification filtering, the nine coastal classification zones were merged into a single national dataset. Each zone corresponds to an independent Random Forest Classification covering a distinct environmental region of the Mexican coastline.

The integration was performed by loading the filtered classification of each coastal zone and combining them into a single image using the Google Earth Engine `mosaic()` function. Since the coastal zones were defined as mutually exclusive geographic units, no spatial overlaps occur among them, allowing the mosaic operation to assign each pixel directly from its corresponding zone without conflicts.

7.2 Mangrove Binary Product

For each year, pixels classified as Mangrove were retained, while all remaining classes were masked. Rather than recoding mangrove pixels to a binary value (1), the product preserves the original land cover class code (Class 5) used in the national MapBiomass Mexico classification. This enables the mangrove layer to be seamlessly overlaid onto the national land cover maps generated by MapBiomass, ensuring compatibility with the official legend while replacing the corresponding land cover class where mangroves are mapped.