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Mapping Coconut Plantations in the Brazilian Semi-Arid Region Using Machine Learning Techniques and Sentinel Imagery

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ABSTRACT:Coconut farming in the Brazilian semi-arid region, especially in the state of Ceará, plays a significant economic role but faces challenges such as the limited use of modern agricultural technologies. The use of remote sensing techniques, through both multispectral satellite imagery and radar data, offers an opportunity to efficiently, quickly, and accurately monitor crop conditions, promoting more effective and sustainable management. This study aimed to map coconut plantations in the municipality of Paraipaba, in the state of Ceará, using machine learning techniques. Multispectral images from Sentinel-2 satellites were used, covering the period from January 1, 2024, to March 8, 2025, and radar images from Sentinel-1 satellites, from January 1, 2023, to May 30, 2024. The study employed Support Vector Machine (SVM) and Random Forest (RF) classifiers, with RF demonstrating superior accuracy in both multispectral and radar images. The RF classifier achieved an accuracy of 97.8% and a kappa coefficient of 94.2% with multispectral images, outperforming SVM, which yielded an accuracy of 86.3% and a kappa of 71.9%. For radar imagery, RF achieved a global accuracy of 98.6% and a kappa of 93.3%. This study highlights the effectiveness of machine learning techniques, particularly RF, for the accurate and efficient mapping of coconut plantations using Sentinel-1 and Sentinel-2 satellite imagery.

KEYWORDS: Coconut plantations, Machine learning, Remote sensing, Sentinel satélites, Semi-aridregions.

I. INTRODUTION

The coconut palm (*Cocos nucifera* L.) is a widelydistributedcropthroughoutthetropics, cultivated in approximately 86 countries, playing a prominent role in food security, income generation, andinternational tradeespeciallyduetothegrowingdemand for freshcoconutwater [1][2]. Brazil ranks fifth in global coconutproduction, witharound 2.4 million tons per year [3], withtheNortheastRegionserving as thecountry’smainproduction hub. In thestateof Ceará, themunicipalityof Paraipaba stands out as thelargestproducer, withanestimated output of 115.5 millionfruits, underscoringtheeconomicand social importanceofcoconutcultivation in thesemi-arid region.

Despite its productiverelevance, coconutfarming in Brazil'sNortheast still lacksrobusttechnologicalstrategies for thesystematic mapping andmonitoringofcultivatedareas. The scarcityofstudiesfocusedonthe use ofadvancedgeospatialtechnologies for crop management represents a critical gap, particularly in regionsaffectedbyclimatevariabilityandstructurallimitations. In thiscontext, remotesensingusing radar andmultispectralimageryhasemerged as a viable, non-destructive, andscalablealternative for extractingbiophysicalvegetationparameters, such as theNormalizedDifferenceVegetation Index (NDVI), whichiswidelyapplied in precisionagriculture [4][5].

Amongthemainadvantagesofremotesensing are its broadspatialcoverage, high temporal frequencyof data acquisition, andindependencefrom prior informationaboutsoilconditionsandproduction systems [6][7]. However, the high computationalcostassociatedwithprocessingtheseimagesremains a challenge, especially in environmentswithlimitedtechnologicalinfrastructure. Cloud computing, throughplatformssuch as Google Earth Engine (GEE), hashelpedtoovercomethisbarrierbyintegrating global geospatial data repositorieswithanalytical tools optimized for large-scaleparallelprocessing [8][9].

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GEE provides direct accesstoimageryfromopticaland radar sensors, includingLandsat, Sentinel-1, Sentinel-2, and MODIS, eliminatingtheneed for specialized hardware andfacilitatingtheimplementationofcomplexanalytical workflows. The Sentinel-1 mission uses C-band syntheticaperture radar (SAR), offeringimageswithvaryingspatialresolutionsdependingontheacquisitionmode, reachingupto 5 meters. The Sentinel-2 mission, with a spatialresolutionof 10 metersand a revisit time ofuptofivedays, hasbecome a strategic tool for agriculturalmonitoring in tropical regions, enablingthedetectionofphenologicalvariationsandaccurateland cover mapping [10][11].

In addition, theincorporationof machine learning (ML) algorithms, such as Random Forest (RF) andSupport Vector Machines (SVM), hasrevolutionizedsupervisedclassification approaches. These models, being non-parametricandindependentofassumptionsregarding data distribution, are particularlyeffective in agriculturalcontextscharacterizedbyspatialandspectralheterogeneity [12][13][14]. Recentliteraturehighlightsthesuccessofcombiningmultispectral data and ML algorithms in small-scalefarming, showingpromisingresults in developing countries [15][16].

Alongsideopticalimagery, syntheticaperture radar (SAR) data, such as thoseprovidedby Sentinel-1, haveenhancedtheanalyticalpotentialofagriculturalmonitoring systems duetotheir cloud penetrationcapabilityandindependencefrom illuminationconditions [17]. Althoughsusceptibletotopographicaldistortions, SAR data complementspectralinformation in discriminating surface features, especially in tropical regions [18].

Moreover, indicessuch as theNormalizedDifferenceBuilt-up Index (NDBI) haveproveneffective in identifyingimpervious surfaces andbuilt-upareas, contributingtotherefinementofclassifications in urban–rural transition zones [19].

In light ofthisscenario, thepresentstudyaimedtomapcoconutcultivationareas in themunicipalityof Paraipaba, Ceará, using radar imageryfromthe Sentinel-1 missionandopticalimageryfrom Sentinel-2, processedonthe Google Earth Engineplatform. The classificationofcoconutcultivationareasemployedthe Random Forest andSupport Vector Machine algorithmstoassesstheaccuracyandapplicabilityofthese approaches withinthecontextofcoconutfarming in the Brazilian semi-arid region.

II. METHODOLOGY

Studyarea

The municipalityof Paraipaba, located in thestateof Ceará, Brazil, issituatedatcoordinates 3° 26' 20" S and 39° 08' 52" W, atan altitude of 39 metersandwith a total areaof 289,231 m² (Figure 1). AccordingtotheKöppenclassification, the local climateisoftypeAw (tropical savannaclimate), characterizedby a dryseason. The regionhasanaverageannualrainfallof 1,131 mm andmaximumandminimumtemperaturesof 31.2 °C and 21.1 °C, respectively [20].

Figure 1. Boundaries of the municipality of Paraipaba

Remote sensing data

Radar imagesfromthe Sentinel-1 satellite, madeavailablebytheEuropean Space Agency (ESA) throughthe Google Earth Engine (GEE) platform, wereused in thisstudy. Sentinel-1 consistsofsatellitesequippedwith C-band (~5.4 GHz) SyntheticAperture Radar (SAR), offering global coverageandspatialresolutionofupto 10 meters.

For thisstudy, imagesacquired in InterferometricWideSwath (IW) modewereselected, using VV and VH polarizations, captured in descendingorbit. The imageswerefilteredbasedontheabsenceofsevereatmosphericinterferenceandspacedat a maximum temporal intervalof 24 days.

The imageswerepre-processed in GEE throughthefollowing steps:

- **Precise orbitcorrection** (similar torecalibratingthesatellite's GPS path toensureaccuratepositioning);
- **Radiometriccalibrationto sigma nought (σ^0)** (standardizingtheradar'sbrightnessvaluesso differentimagesspeakthesame "language");
- **Specklefilteringusing a 3×3 Lee filter** (like smoothing out "staticnoise" on a TV screentorevealthe real picture);
- **Geometriccorrectionandorthorectificatio nusingthe SRTM elevation model** (correcting for terraindistortions, similar toflattening a crumpledmap);
- **Logarithmicconversiontodecibels (dB)** (transformingthe data scaletobetter compare values, like adjustingsoundlevelsto a decibel scale for clarity).

Constructionofthe training andvalidationdataset

Georeferenced samples ofareaswithandwithoutcoconutcultivationwerecollec tedbasedon high-resolutionimageryavailable in Google Earth Engine (GEE). These samples weredividedintotwodatasets:

- **Training set (70% ofthe samples):**usedtotrainthealgorithms;
- **Validation set (30%):**usedtoassessclassificationaccuracy.

The samplingfollowed a stratifiedrandom model, ensuringproportionalrepresentationbetween classes andminimizingspatial bias.

Supervisedclassification

The classificationofcoconutcultivationareaswasperforme dusingtwowidelyrecognized machine learning algorithms:

- **Random Forest (RF):**analgorithmbasedonan ensemble ofdecisiontreesbuiltfromrandomsubsetsofth edataset. The numberoftreesandthemaximumdepthwere fine-tunedthroughcross-validation.
- **Support Vector Machine (SVM):**analgorithmbasedonmaximizingthe marginbetweenhyperplanes. The Radial BasisFunction (RBF) kernel wasused, withoptimizationoftheparameters$C$andγperf ormed via grid search.

Both models wereimplementedonthe Google Earth Engine (GEE) platform, usingbackscattervalues (σ^0 , VV, and VH) andtheratiobetweenpolarizations (VV/VH) to improve classifier performance.

Accuracy assessment

Model accuracywasevaluatedusingconfusionmatricesandsta tisticalmetrics, including:

- Overall accuracy;
- Kappa coefficient (K);
- User'sAccuracyandProducer'sAccuracy for eachclass;
- Omissionandcommissionerrors.

Additionally, classificationmapsweregeneratedto visualize theclassifiedareasandidentifyboundariesbetween classes.

Satelliteimagery

Multispectralimagesofthestudyarea, acquiredbythe Sentinel-2 satellites, wereused for theperiodfromJanuary 1, 2024, toMarch 8, 2025, toidentifyareasundercoconutcultivation. Sentinel-2 imageshave a spatialresolutionof 10 meters, a temporal resolutionof 5 days, and a radiometricresolutionof 12 bits per pixel, meaningthattheintensityofeach pixel ranges from 0 to 4096 graylevels, ensuring a high levelofdetail in thegeneratedinformation.

Toensurebetter data processingquality, multispectralimagescapturedondayswithlow cloud cover wereselected. The cloud filteravailableonthe GEE platformwasappliedusingthecommandfilter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 2)). Thiscommandselectsimageswithlessthan 2% cloud cover over the total imagearea.

Biophysicalparameters

The algorithms for processingbiophysicalparameterswereimplementedo nthe Google Earth Engine (GEE) platform. GEE waschosendueto its capabilitytoefficientlyaccessandprocesslarge

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volumes ofremotesensing data, enabling fast andreproducibleanalyses.

The processingwasconducted in thefollowing steps:

- **Data acquisition:**multispectralimagesfromthe Sentinel-2 satellites, available in the GEE catalog, wereused.
- **Pre-processing:**thisincludedatmosphericcorrectionand cloud filteringtoensureimagequality.
- **Calculationofvegetationindices (VIs):**indicessuch as NDVI, NDBI, andothersrelevanttomonitoringthecoconutorchardwerecomputed.

Vegetationindices (VIs)

The multispectralimagesfromthe Sentinel-2 satellitesprovidethespectral bands necessary for calculatingvariousvegetationindices (VIs).

The processingandcalculationofVIswereperformedonthe Google Earth Engine (GEE) platform, whichisrecognized for its efficiency in analyzinglarge volumes of data andenablingprocessautomation. Aftercalculation, thematic VI mapsweregeneratedto visualize andidentifyspatialpatternsand trends withinthestudyarea.

There are categoriesofVIsrelatedtostructural, biochemical, andphysiologicalaspects (associatedwith stress), as well as thosespecifictopestanddiseasedetection. The VIsutilized in thisstudy are listedbelow (Table 1).

Statisticalanalysis

Thematicmapsweregeneratedtoillustratethe spatialdistributionofthevegetationindices (VIs), promoting clear visual interpretationofthe data andfacilitatingtheir use in theclassifiers.

Confusionmatricesandthe Kappa statisticwereemployedtoassesstheaccuracyoftheestimatedcoconutcultivationarea. Classificationaccuracywasdeterminedbycomparing pixel allocations in theclassifiedimagewithcorrespondingreference data. A confusionmatrixwasconstructedto compile pixels ofagreementanddisagreement, withrowsandcolumnsrepresentingall classes, andmatrixelementsindicating pixel counts in thetestdataset. Accuracymetrics, such as overall accuracyandthe Kappa coefficient, werederivedfromtheerrormatrix.

Overall accuracy (OA) wascalculatedusing Equation 1.

$$OA = \frac{P_o}{P_n} \text{x } 100 \qquad \text{Equation 1}$$

Where **Pn**isthe total numberof pixels and**Po**isthe total numberofcorrectlyclassified pixels.

Consideringt**N** as the total numberof pixels analyzed; **Nii** as thenumberof pixels correctlyclassified for class*i*; **Ni.** as the total numberof pixels classified as class*i* (sum ofrow*i* in theconfusionmatrix); and**N.i** as the total numberof pixels thattrulybelongtoclass*i* (sum ofcolumn*i* in theconfusionmatrix).

Thus, theproportionofobservedagreement**Po** (Equation 2) andtheproportionofexpectedagreementby chance **Pe** (Equation 3) are calculated, respectively, by:

$$P_o = \frac{\sum N_{ii}}{N} \qquad \text{Equation 2}$$

$$P_e = \frac{\sum (N_{i.} . N_{.i})}{N^2} \qquad \text{Equation 3}$$

To evaluate the effectiveness of the classifiers, the Kappa statistic is a robust method that allows a comparative analysis of the results from maps obtained through remote sensing, within certain limits [23]. The Kappa coefficient (K) is calculated using Equation 4.

$$K = \frac{P_o - P_e}{1 - P_e} \qquad \text{Equation 4}$$

III. RESULTS

The mapping resultsindicatedthespatialdistributionofcoconutcultivationareas in themunicipalityof Paraipaba, Ceará state. Generally, coconut palms are cultivatedthroughoutalmosttheentiremunicipality, with a higherconcentration in the central region. The spatialdistributionsofcoconut plantations wererelativelydispersedacrossthe central, northern, andsouthernareas (Figures 2 and 3).

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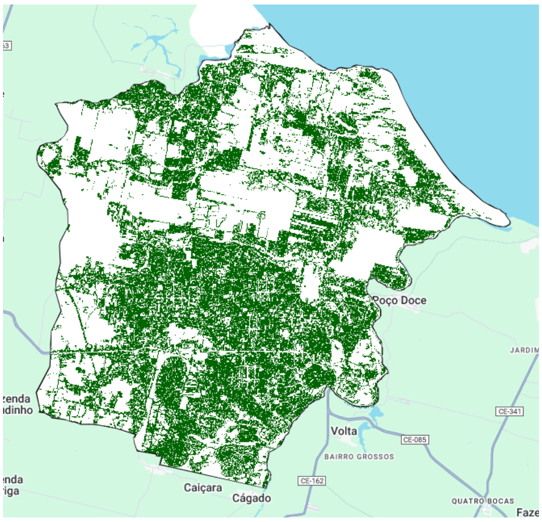

Figure 2. Classification result using the SVM classifier.

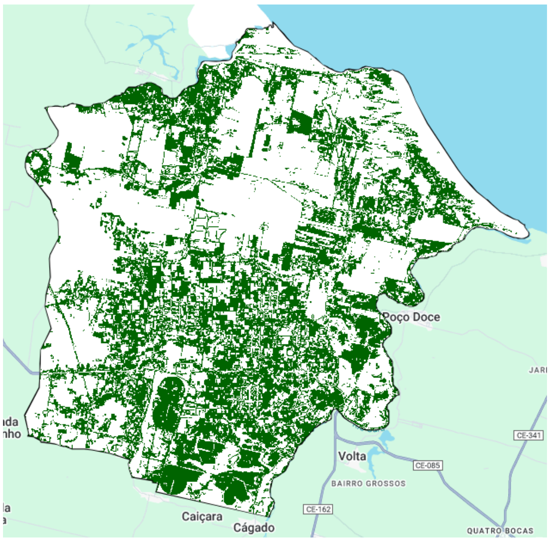

Figure 3. Classification result using the RF classifier.

In thetestedscenarios, thevegetationindices NDVI, mNDVI, and NDBI wereused. The NDVI and NDBI vegetationindicesyieldedthebestclassificationresults (Figure 3), both for opticaland radar images (Figure 4). The bestclassifierwas Random Forest (RF). The RF classificationusingoptical data achievedan Overall Accuracyand Kappa of 97.8% and 94.2%, respectively (Figure 3), outperformingthe SVM classification, whichreachedan Overall Accuracyof 86.3% and a Kappa of 71.9%. The RF classificationof radar imagesobtainedan Overall Accuracyand Kappa of 98.6% and 93.3%, respectively (Figure 4).

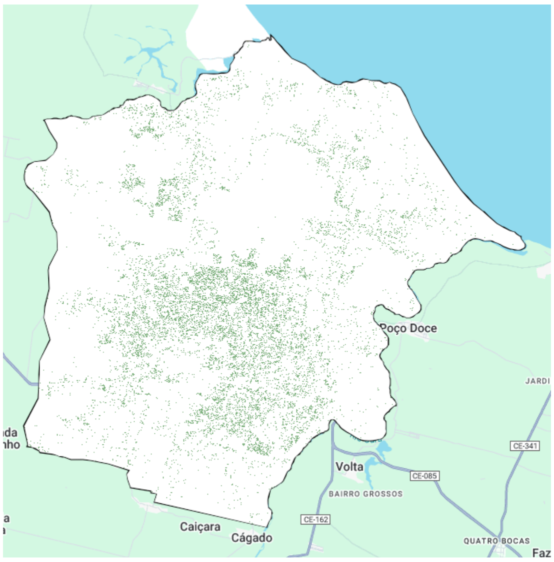

Figure 4. Classificationresultusingthe RF classifierwith radar images.

Table 1. Vegetation indices used.

Index	Equation	Characteristics	Reference
Normalized Difference Vegetation Index (NDVI).	$\frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R}$	Structural index related to biomass production.	[21]
Modified Normalized Difference Vegetation Index (mNDVI).	$\frac{\rho_{NIR} - \rho_{RedEdge}}{\rho_{NIR} + \rho_{RedEdge}}$		[22]
Normalized Difference Built-up Index (NDBI).	$\frac{(\rho_{SWIR2} - \rho_{NIR})}{(\rho_{SWIR2} + \rho_{NIR})}$	Index adjusted to extract information about impervious surfaces in urban areas.	[19]

IR: infrared; R: red; ρ: reflectanceatspecificwavelength; SWIR2: surface reflectanceofthesecondshortwaveinfrared band; NIR: surface reflectanceofthenear-infrared band.
Source: author.

IV. DISCUTION

Basedonthemetricsof Overall Accuracyandthe Kappa coefficient, thepoorestresultwasobtainedwiththe SVM classifierusingmultispectralimagesfromthe Sentinel-2 satellites. The SVM classifiershowedsignificantdifficulty in distinguishingpastureareasfromcoconutcultivationareas, achieving a Kappa of 71.9%. The RF classifierwasbetterabletodifferentiatebetweenpasture andcoconutcultivationareas. The texture characteristicwasbettercapturedbythe RF classifierwhenusingmultispectralimages.

Using radar images, the RF classifieralsoachievedbetterclassificationmetrics for coconutcultivationareas, with a Kappa of 93.3%. It isnoteworthythatthe RF classifierwith radar imagesfromthe Sentinel-1 satelliteclassifiedcoconutareasintosmallerclassificationunits (Figure 4); however, thecoconutcultivationregionscorrespondedtothesame areasidentifiedwithmultispectralopticalimagery.

The NDVI and NDBI vegetationindicesprovidedthestrongestsupport for imageclassification, both for opticaland radar images. The NDVI index, amongothereffects, highlightsregions in theimageswithphotosyntheticallyactiveplantsanddistinguishesthemfromsenescentvegetation, which helps theclassifiertosegmentcoconutcultivationareasfromotherland uses. The NDBI index highlightsregionswithimpervious surfaces, such as urbanareas, thusfacilitatingtheclassifier in separatingimperviousareasfrompermeableareascultivatedwithcoconut palms.

V. CONCLUSION

The resultsobtained in thisstudydemonstratetheeffectivenessofapplyingremotesensingtechniquesand machine learning algorithmstomapcoconutcultivationareas in themunicipalityof Paraipaba, Ceará. Amongtheevaluatedmethods, the Random Forest (RF) classifiershowedthebest performance, particularlywhenappliedto radar imagesfrom Sentinel-1, achievingan Overall Accuracyof 98.6% and a Kappa coefficientof 93.3%.

The superiorityof RF over SVM wasevident in distinguishingbetweenpastureareasandcoconut plantations, especiallyduetothealgorithm'sabilitytohandlethespectralandtexturalvariabilityoftheimages. The vegetationindices NDVI and NDBI significantlycontributedtoclassificationaccuracybyimprovingclassseparability, highlightingkey features such as photosyntheticallyactivevegetationandimpervious surfaces.

The integrationofopticaland radar imagery, combinedwithrobustclassifiers, proves tobe a promisingstrategy for monitoringperennialcrops in tropical semi-aridregions. The findingsofthisstudycansupportagriculturalplanning, land management, andthedevelopmentofpublic policies aimedatstrengtheningthecoconutproductionchain in semi-aridregions.

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