



Tutorial para mapear distúrbios florestais no sudoeste da Amazônia usando CODED, LandTrendr e MTDD

SERVIR  **AMAZONIA**

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Tutorial para mapear distúrbios florestais no sudoeste da Amazônia usando CODED, LandTrendr e MTDD

1. Histórico

Devido à necessidade urgente de compreender os efeitos dos distúrbios florestais sobre os serviços dos ecossistemas, vários algoritmos de sensoriamento remoto focados na detecção de mudanças na vegetação foram desenvolvidos na última década. O desafio agora está em compreender qual algoritmo melhor se adapta à área de estudo do usuário e ao objetivo da pesquisa. Este tutorial compartilha nosso trabalho do Google Earth Engine (GEE) derivado da avaliação do desempenho de três algoritmos - Detecção de Degradação Contínua (CODED), Detecção de Tendências de Distúrbios e Recuperação (LandTrendr) baseada em Landsat, e Detecção de Perturbações de Tempo Multi-variável (MTDD) - para detectar e caracterizar perturbações florestais no sudoeste da Amazônia (SWA). Para todo o estudo, consulte Reygadas et al. (2021) (atualmente em revisão).

Na seção 3.3, compartilhamos códigos GEE baseados no MTDD para mapear distúrbios no SWA (isto é, Ucayali, Peru e Acre, Brasil). Tutoriais GEE completos para CODED e LandTrendr estão disponíveis gratuitamente online; neste tutorial, compartilhamos a configuração-parametrização específica para o SWA.

2. Definições

Embora seja difícil adotar um conjunto de definições que se harmonizem com a lógica fundamental por trás de cada algoritmo, nos referimos ao desmatamento, à degradação florestal e aos distúrbios florestais da seguinte forma:

- **Desmatamento.** Conversão de longo prazo ou permanente de terras florestadas em terras não florestadas (FAO, 2001).

- **Degradação das florestas.** Embora não haja uma definição amplamente aceita, geralmente é considerado um processo de longo prazo que não leva a uma mudança na cobertura da terra, mas afeta negativamente a estrutura e função da floresta (Sasaki e Putz, 2009; Schoene et al., 2007).

- **Distúrbios florestais.** Fatores que impulsionam o estado e função da floresta que podem variar de eventos de alto impacto, como incêndios ou desmatamento, a processos sutis e graduais, como os causados por secas prolongadas, insetos ou doenças (Cohen et al., 2017; McDowell et al., 2015).

Assim, consideramos tanto o desmatamento (ou seja, evento de alto impacto) quanto a degradação florestal (ou seja, processo sutil e gradual) tipos de distúrbios florestais.

3. Algoritmos

Os três algoritmos usam valores de reflexão de superfície do Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper+ (ETM+) e Landsat Operational Land Imager (OLI).

3.1. CODED

O CODED v0 utiliza séries temporais de frações de membros e NDFI para detectar e caracterizar distúrbios que podem mais tarde ser classificados como degradação ou desmatamento. Veja Bullock et al. (2020) para detalhes do algoritmo e Bullock (2020) para a implementação do GEE.

3.1.1. Mapa de distúrbios

Esta seção demonstra como executar este código para produzir um mapa de distúrbios florestais.

Insumos

O usuário tem que inserir as seguintes entradas:

```

CODED_DisturbancesMap
Get Link Save Run Reset Apps

Imports (2 entries)
var studyArea: Table users/retinta/Tutorials/CaseStudy1
var trainingPts: Table users/retinta/Tutorials/TrainingPointsCODED

1 // ===== CODED ALGORITHM =====
2 // Retrieves a forest disturbances map
3 // See Bullock et al., 2020 for algorithm details, and Bullock, 2020 for GEE implementation
4 // This particular piece of code to obtain CODED outputs was written by V. Reygadas and V. Galati
5
6 // ===== User-defined Information =====
7
8 // Defines the study area
9 var saveRegion = ee.FeatureCollection(studyArea);
10
11 // Defines training data
12 var trainingData = trainingPts;
13
14 // Defines parameters
15 var params = ee.Dictionary({
16   'cftThreshold': .01, // Minimum threshold to remove clouds based on cloud fraction
17   'consec': 4, // Number of consecutive observations below the change threshold needed to declare a disturbance
18   'thresh': 3, // Change threshold (observation residual normalized by the training model) RMSE
19   'start': 2000, // Start year of the study period
20   'end': 2018, // End year of the study period
21   'trainDataEnd': 2016, // End year of the training period
22   'trainDataStart': 2013, // Start year of the training period
23   'trainLength': 3, // Number of years in the training period
24   'soil': [2000, 3000, 3400, 5800, 6000, 5800], // Soil endmember reflectance value for each band
25   'gv': [100, 900, 400, 6100, 3000, 1000], // Green vegetation endmember reflectance value for each band
26   'npv': [1400, 1700, 2200, 3000, 5500, 3000], // Non-photosynthetic vegetation endmember reflectance value for each band
27   'shade': [0, 0, 0, 0, 0, 0], // Shade endmember reflectance value for each band
28   'cloud': [9000, 9600, 8000, 7800, 7200, 6500], // Cloud endmember reflectance value for each band
29   'forestLabel': 1, // Label assigned to forest in the training data
30   'window': 2, // Maximum number of years to use in the monitoring period at any given time
31   'minYears': 2, // Minimum years between disturbances
32   'numChanges': 1, // Maximum number of changes to output
33   'minObs': 5, // Minimum number of observations needed to fit a model for training
34 });
35
36 // Defines output name
37 var outputName = 'CODED_Disturbances';
38

```

Executando o Código

Execute o código clicando em run. Uma vez terminado, vá até o console de tarefas e clique em run para exportar os resultados como um ativo GEE e como um raster.

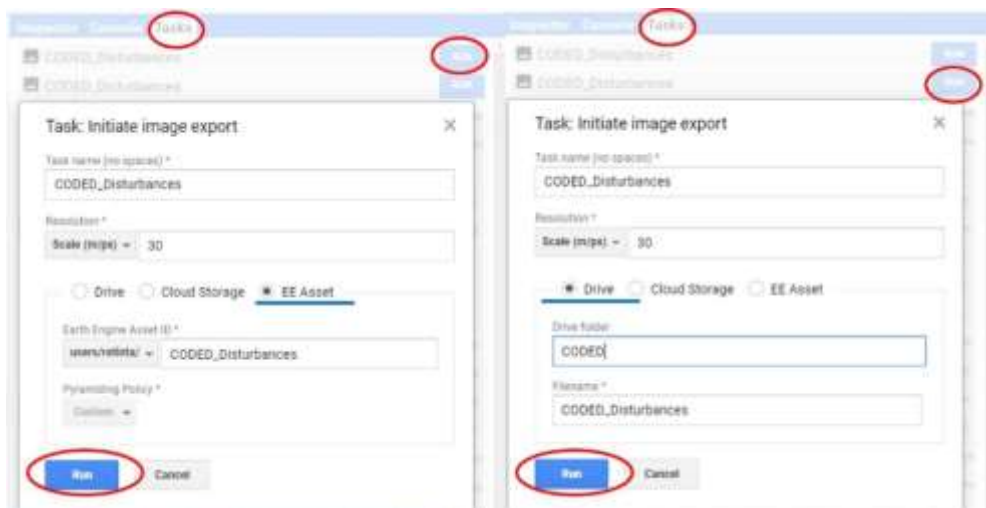
```

39 ///////////////////////////////////////////////////Gets CODED main results////////////////////////////////////
40
41 // Adds CODED utility functions
42 var codedUtils = require('users/retinta/Tutorials:CODED_changeDetection');
43 var dataUtils = require('users/retinta/Tutorials:CODED_dataUtils');
44
45 // Runs CODED
46 var results = codedUtils.submitCODED(saveRegion, params, trainingData);
47
48 // Turns array columns into images
49 var disturbances = dataUtils.makeImage(results, 0, 'dist_', params.get('start'), params.get('end'));
50 var magnitude = dataUtils.makeImage(results, 1, 'mag_', params.get('start'), params.get('end'));
51 var postChange = dataUtils.makeImage(results, 2, 'post_', params.get('start'), params.get('end'));
52 var difference = dataUtils.makeImage(results, 3, 'dif_', params.get('start'), params.get('end'));
53 var forestFlag = dataUtils.makeImage(results, 4, 'forest_', params.get('start'), params.get('end'));
54
55 var disturbanceBands = disturbances.addBands([magnitude, postChange, difference]);
56
57 var save_output = ee.Image(dataUtils.reduceBands(ee.Image(disturbanceBands), params)
58   .addBands(forestFlag.select(0)) // Forest flag for first year
59   .setMulti(params));
60
61 /////////////////////////////////////////////////// Exports the results //////////////////////////////////////
62
63 //Exports results as a GEE asset
64 = Export.image.toAsset({
65   image: save_output,
66   description: outputName,
67   assetId: outputName,
68   maxPixels: 1e11,
69   scale: 30,
70   region: saveRegion,
71   pyramidingPolicy: {
72     'default': 'mode'
73   }
74 });
75
76 //Exports results as a raster to drive
77 = Export.image.toDrive({
78   image: save_output,
79   description: outputName,
80   region: saveRegion,
81   scale: 30
82 });
83
84 ///////////////////////////////////////////////////
85 print("All done");

```

Detects disturbances and estimates their characteristics

Exports the results as a GEE asset (used as input of the degradation/deforestation map) and as a raster (can be visualized in any GIS)



Output

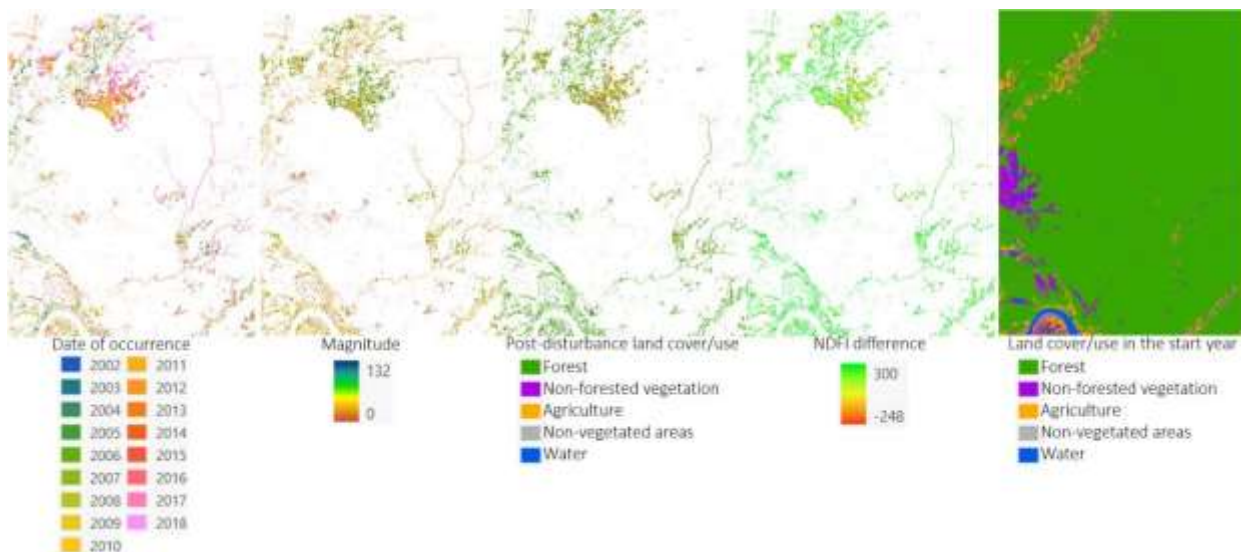
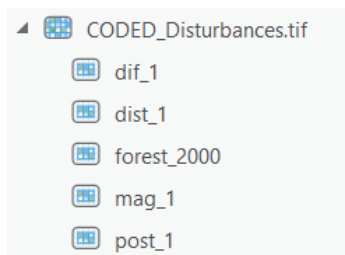
Este código produz um mapa de perturbações com quatro camadas por perturbação (isto é, data de ocorrência, magnitude da mudança, cobertura da terra após a perturbação, diferença NDFI

de antes e depois da perturbação) e uma última camada indicando o tipo de cobertura da terra no ano inicial.

GEE asset



Raster (".tif" file)

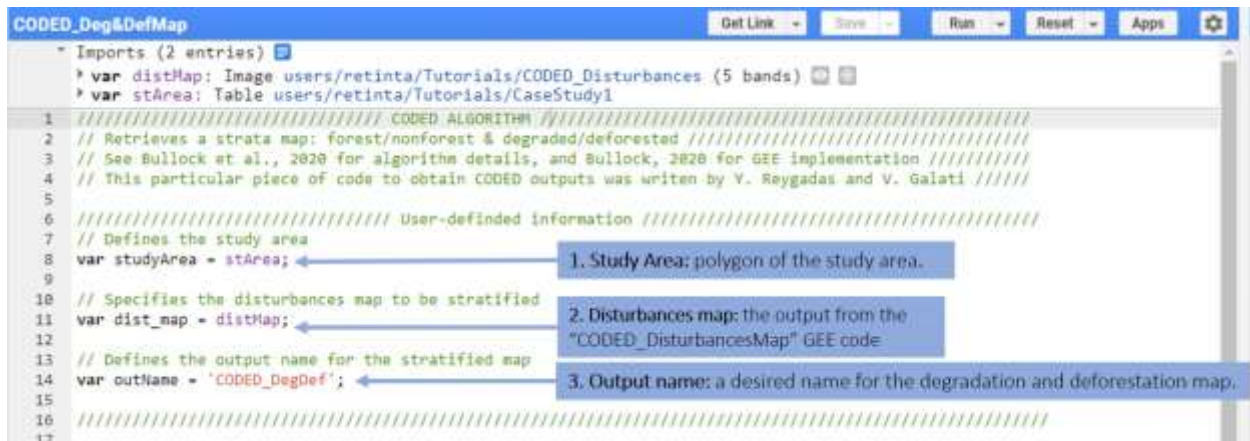


3.1.2. Mapa de degradação e desmatamento

Esta seção demonstra como executar este código para produzir um mapa classificado em floresta, não floresta, degradação e desmatamento.

Insumos

Há três entradas que o usuário tem que entrar:



```
CODED_Deg&DefMap
Get Link Save Run Reset Apps

Imports (2 entries)
var distMap: Image users/retinta/Tutorials/CODED_Disturbances (5 bands)
var stArea: Table users/retinta/Tutorials/CaseStudy1

1 /////////////////////////////////////////////////// CODED ALGORITHM //////////////////////////////////////////
2 // Retrieves a strata map: forest/nonforest & degraded/deforested //////////////////////////////////////////
3 // See Bullock et al., 2020 for algorithm details, and Bullock, 2020 for GEE implementation //////////////////////////////////////////
4 // This particular piece of code to obtain CODED outputs was written by V. Reygadas and V. Galati //////////////////////////////////////////
5
6 /////////////////////////////////////////////////// User-defined information //////////////////////////////////////////
7 // Defines the study area
8 var studyArea = stArea;
9
10 // Specifies the disturbances map to be stratified
11 var dist_map = distMap;
12
13 // Defines the output name for the stratified map
14 var outName = 'CODED_DegDef';
15
16 //////////////////////////////////////////
17
```

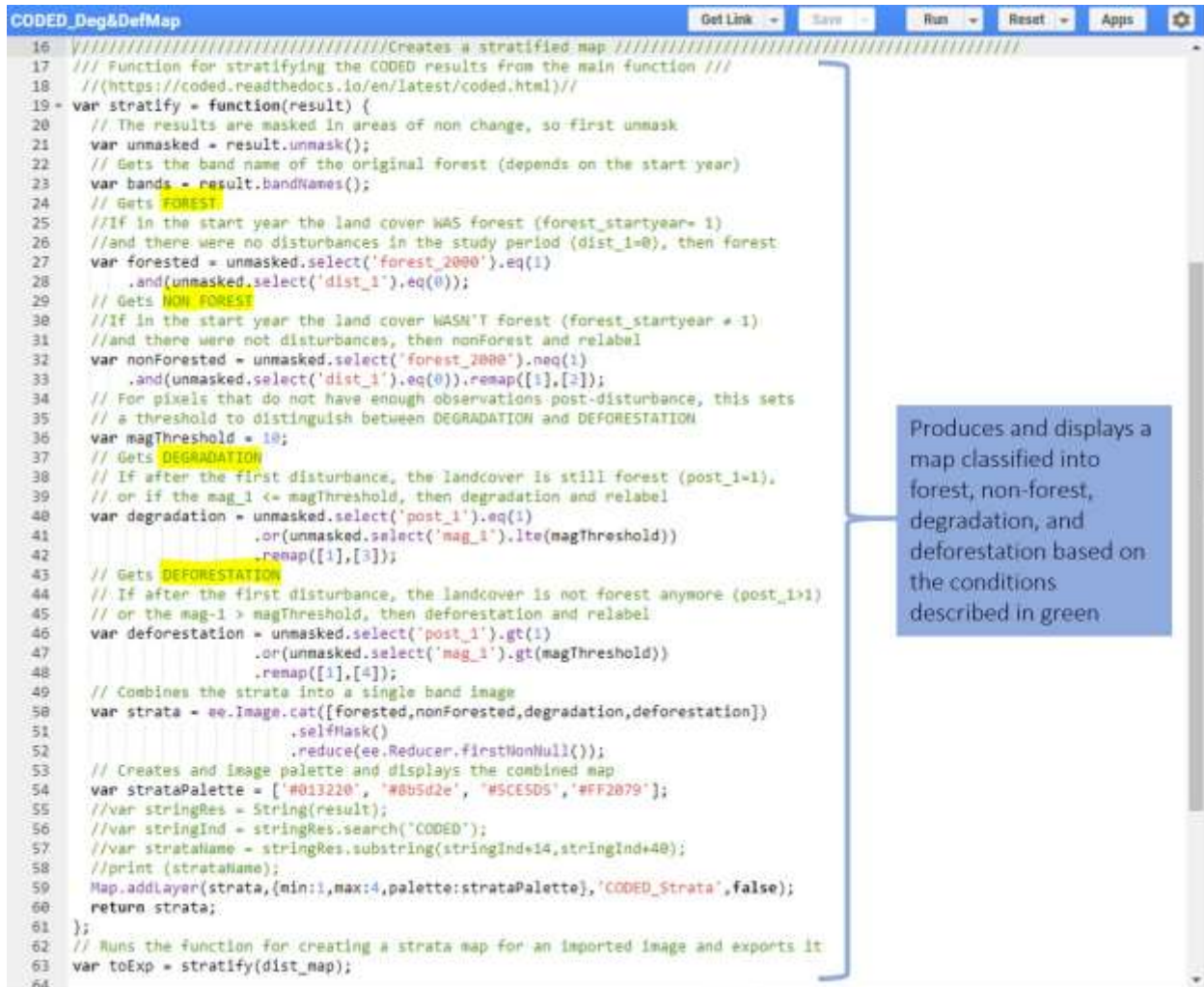
1. Study Area: polygon of the study area.

2. Disturbances map: the output from the "CODED_DisturbancesMap" GEE code

3. Output name: a desired name for the degradation and deforestation map.

Executando o Código

Execute o código clicando em run. Uma vez terminado, vá até o console de tarefas e clique em run para exportar os resultados como um raster.



```
16 //////////////////////////////////////////////////Creates a stratified map //////////////////////////////////////////
17 // Function for stratifying the CODED results from the main function //
18 // (https://coded.readthedocs.io/en/latest/coded.html) //
19 var stratify = function(result) {
20   // The results are masked in areas of non change, so first unmask
21   var unmasked = result.unmask();
22   // Gets the band name of the original forest (depends on the start year)
23   var bands = result.bandNames();
24   // Gets FOREST
25   // If in the start year the land cover WAS forest (forest_startyear= 1)
26   // and there were no disturbances in the study period (dist_1=0), then forest
27   var forested = unmasked.select('forest_2000').eq(1)
28     .and(unmasked.select('dist_1').eq(0));
29   // Gets NON-FOREST
30   // If in the start year the land cover WASN'T forest (forest_startyear != 1)
31   // and there were no disturbances, then nonForest and relabel
32   var nonForested = unmasked.select('forest_2000').neq(1)
33     .and(unmasked.select('dist_1').eq(0)).renap([1],[2]);
34   // For pixels that do not have enough observations post-disturbance, this sets
35   // a threshold to distinguish between DEGRADATION and DEFORESTATION
36   var magThreshold = 10;
37   // Gets DEGRADATION
38   // If after the first disturbance, the landcover is still forest (post_1=1),
39   // or if the mag_1 <= magThreshold, then degradation and relabel
40   var degradation = unmasked.select('post_1').eq(1)
41     .or(unmasked.select('mag_1').lte(magThreshold))
42     .renap([1],[3]);
43   // Gets DEFORESTATION
44   // If after the first disturbance, the landcover is not forest anymore (post_1!=1)
45   // or the mag_1 > magThreshold, then deforestation and relabel
46   var deforestation = unmasked.select('post_1').gt(1)
47     .or(unmasked.select('mag_1').gt(magThreshold))
48     .renap([1],[4]);
49   // Combines the strata into a single band image
50   var strata = ee.Image.cat([forested,nonForested,degradation,deforestation])
51     .selfMask()
52     .reduce(ee.Reducer.firstNonNull());
53   // Creates and image palette and displays the combined map
54   var strataPalette = ['#013220', '#8b5d2e', '#5c5c5c', '#ff2879'];
55   //var stringRes = String(result);
56   //var stringInd = stringRes.search('CODED');
57   //var strataName = stringRes.substring(stringInd+14,stringInd+40);
58   //print (strataName);
59   Map.addLayer(strata,{min:1,max:4,palette:strataPalette},'CODED_Strata',false);
60   return strata;
61 };
62 // Runs the function for creating a strata map for an imported image and exports it
63 var toExp = stratify(dist_map);
64
```

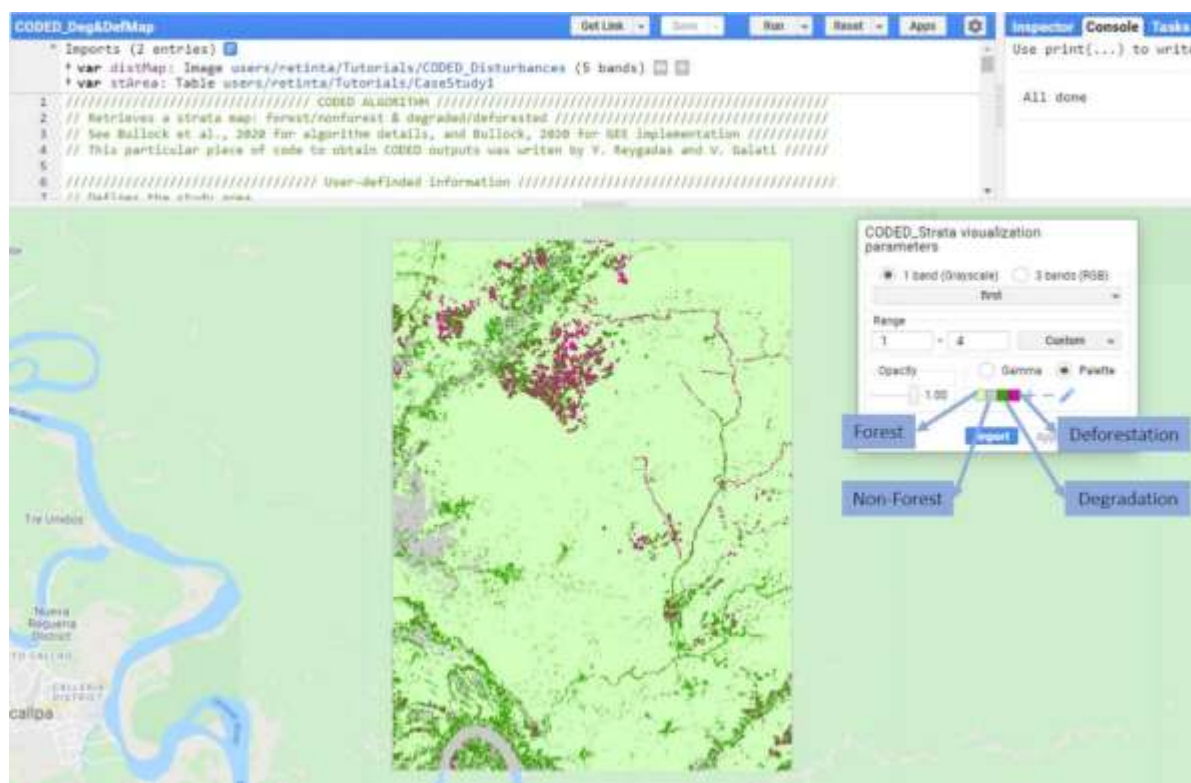
Produces and displays a map classified into forest, non-forest, degradation, and deforestation based on the conditions described in green.



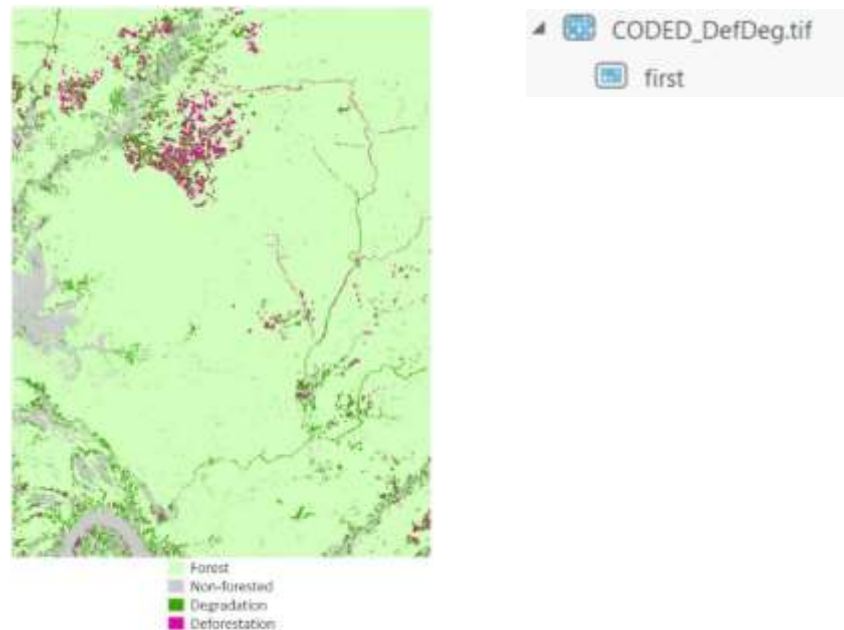
Saída

Este código produz um mapa classificado em floresta, não floresta, degradação e desmatamento.

Mapa exibido em GEE



Raster (".tif" file)



3.2. LandTrendr

LandTrendr detecta e caracteriza a perda ou ganho de vegetação segmentando e ajustando as trajetórias temporais de uma variável definida pelo usuário (possíveis variáveis de entrada: NDFI*added, NBR, NDVI, NDSI, NDMI, TCB, TCG, TCW, TCA, e Landsat TM - bandas equivalentes 1-5 e 7). Veja Kennedy et al. (2010) para detalhes do algoritmo e Kennedy et al. (2018) para implementação do GEE.

3.2.1. Mapa de distúrbios

Esta seção demonstra como executar este código para produzir um mapa de distúrbios florestais.

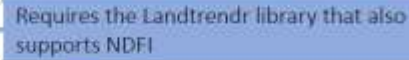
Insumos

O usuário tem que inserir as seguintes entradas:

The image shows a screenshot of a code editor displaying the 'LT_DisturbancesMap' script. Five blue callout boxes with white text and arrows point to specific lines of code, explaining the purpose of different input parameters:

- 1. Input variable(s) to be segmented and from which vegetation changes will be detected:** Points to line 8: `var indices = ['NDVI']; // Input variable(s) to be segmented`
- 2. Parameters to build an annual collection of Landsat surface reflectance from which input variable-time series are calculated:** Points to lines 11-16, which define collection parameters like `startYear`, `endYear`, `startDay`, `endDay`, `area`, and `maskThese`.
- 3. Parameters to control the segmentation of the input variable(s):** Points to lines 20-35, which define segmentation parameters like `maxSegments`, `spikeThreshold`, `vertexCountOvershoot`, `preventOneYearRecovery`, `recoveryThreshold`, `pvalThreshold`, `bestModelProportion`, and `minObservationsNeeded`.
- 4. Parameters to filter vegetation changes:** Points to lines 37-45, which define filtering parameters like `delta`, `sort`, `year`, `mag`, `dur`, `preval`, and `mmu`.
- 5. Output name and folder: a desired name for the disturbances map and the desired output folder in Google drive:** Points to lines 47-51, which define `outName` and `outFolder`.

Execute o código clicando em run. Uma vez terminado, vá até o console de tarefas e clique em run para exportar os resultados como um raster.



Segments the input variable(s)

Produces a disturbances map with the user-defined filtering criteria

Exports the results as raster(s)

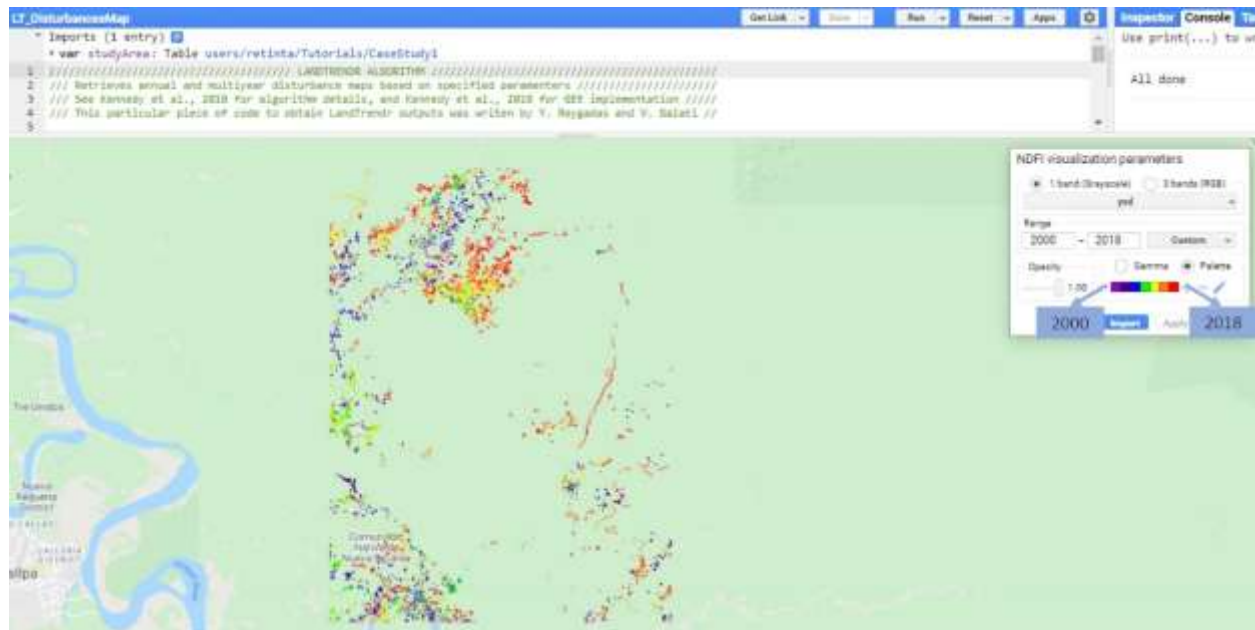
Sets the map visualization parameters

Runs all functions

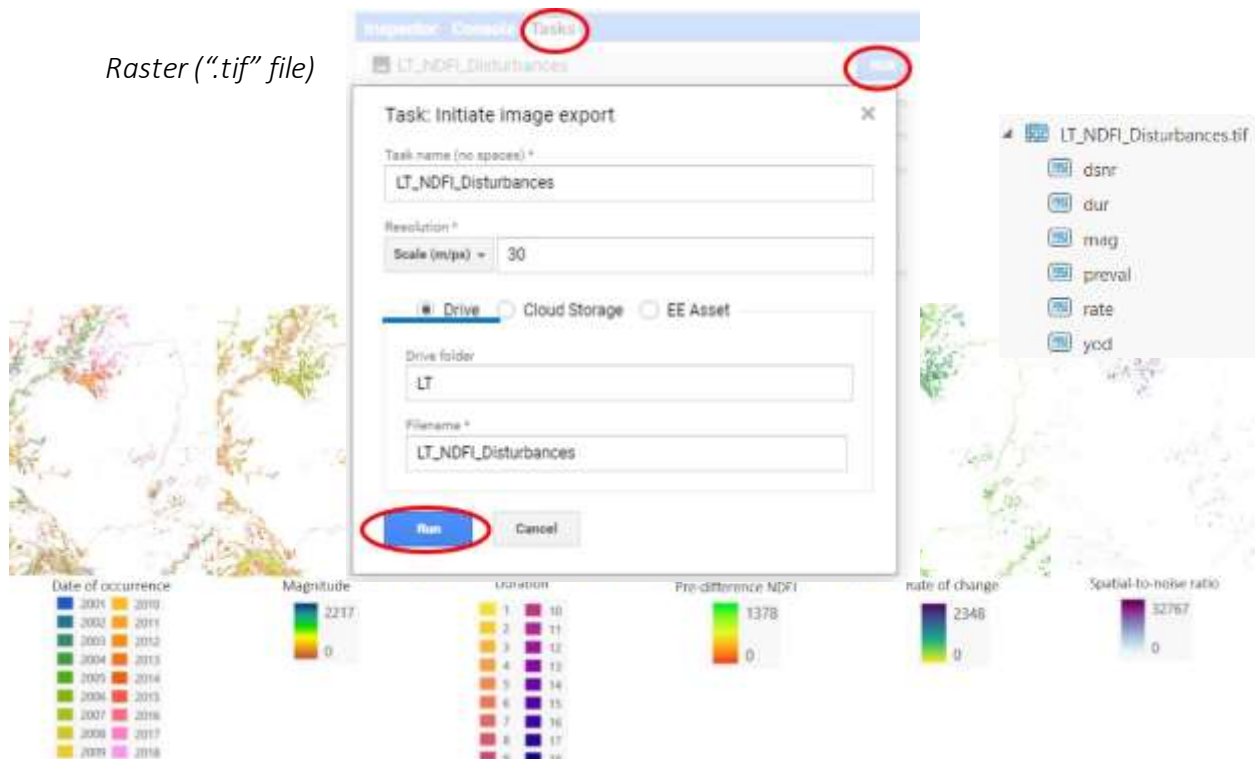
Saída

Este código produz um mapa de perturbações com seis camadas: data de ocorrência, magnitude da mudança, duração, valor espectral antes da mudança, taxa de mudança e relação sinal/ruído.

Mapa exibido em GEE (apenas a camada "ano de perturbação")



Raster (".tif" file)



3.3. MTDD

Este algoritmo baseado no MTDD classifica inicialmente as áreas florestais em intactas, degradadas e desmatadas através do treinamento de um modelo florestal aleatório com sessenta e seis métricas derivadas de seis séries temporais anuais (ou seja, NDVI, duas regiões espectrais SWIR, dois índices NDWI e SAVI) a partir das quais são calculadas onze estatísticas descritivas (ou seja, mínimo, máximo, intervalo, média, desvio padrão, coeficiente de variação, curtose, inclinação, inclinação, inclinação máxima de 5 anos e valor mais recente). Construímos este código MTDD GEE com base em Wang et al. (2019) e o adaptamos ao SWA.

3.3.1. Amostras de treinamento

Esta seção demonstra como executar este código para produzir amostras que são posteriormente utilizadas para treinar um classificador florestal aleatório.

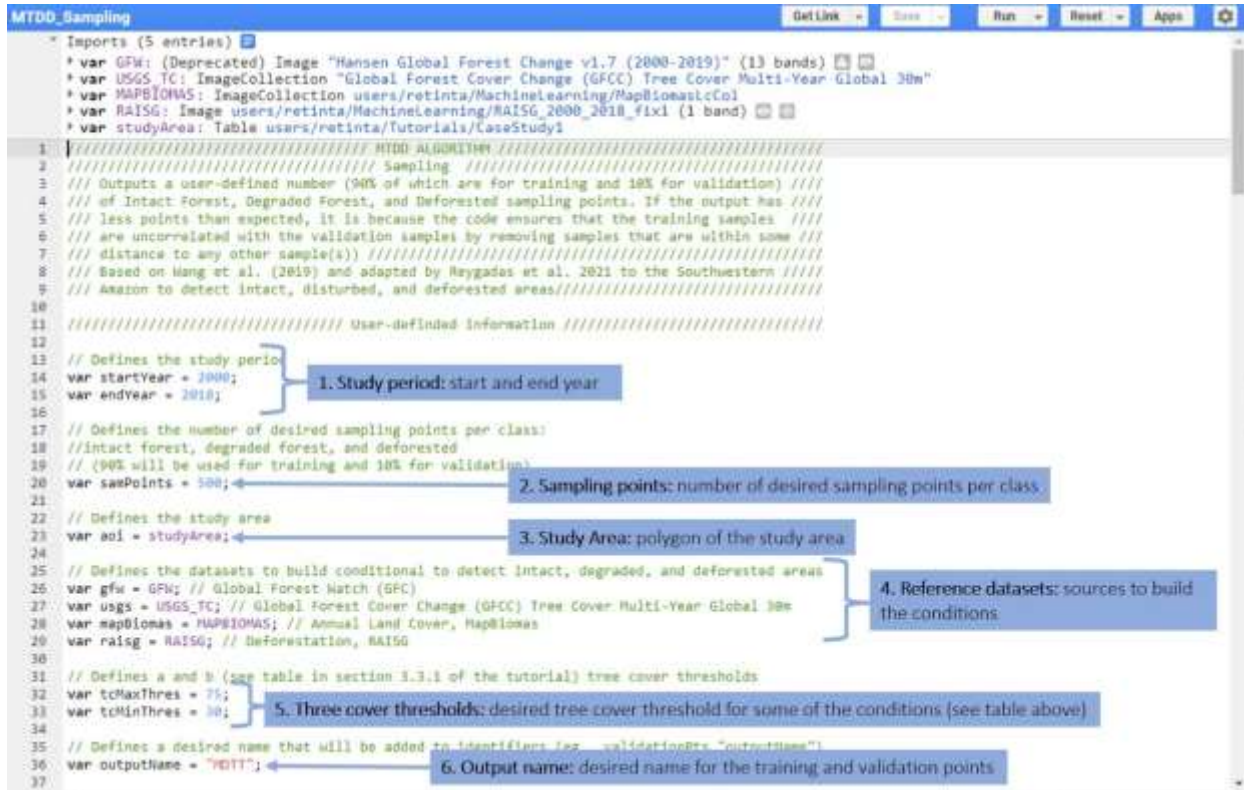
As amostras são selecionadas aleatoriamente a partir do seguinte conjunto de condições:

Classe	Condição	Dados de referência
Intacta	Cobertura florestal em todo o período de estudo	MapBiomas (MapBiomas, 2020)
	Nenhum desmatamento em todo o período de estudo	RAISG (RAISG, 2020)
	Nenhuma perda florestal em todo o período de estudo	GFC (Hansen et al., 2013)
	Cobertura de árvores superior a 75% ^a em 2000	GFC (Hansen et al., 2013)
	Cobertura de árvores superior a 75% ^a em 2015	GFCC (Sexton et al., 2013)
Degradada	Cobertura florestal no final do ano	MapBiomas (MapBiomas, 2020)
	Desmatadas em algum momento do período de estudo	RAISG (RAISG, 2020)
	Cobertura de árvores superior a 30% ^b e inferior a 75% ^a em 2015	GFCC (Sexton et al., 2013)
Deforestada	Nenhuma cobertura florestal no final do ano	MapBiomas (MapBiomas, 2020)
	Desmatadas em algum momento do período de estudo	RAISG (RAISG, 2020)
	Perda florestal em algum momento do período de estudo	GFC (Hansen et al., 2013)

^a e ^b limiares de cobertura de árvores podem ser modificados no código GEE

Insumos

O usuário tem que inserir as seguintes entradas:



```
MTDD_Sampling
Get Link
Tools
Run
Reset
Apps

Imports (5 entries)
* var gfw: (Deprecated) Image "Hansen Global Forest Change v1.7 (2000-2019)" (13 bands)
* var USGS_TC: ImageCollection "Global Forest Cover Change (GFCC) Tree Cover Multi-Year Global 30m"
* var MAPBIOMAS: ImageCollection users/retinta/Machinelearning/MapBiomasCol
* var RAISG: Image users/retinta/Machinelearning/RAISG_2000_2018_fix1 (1 band)
* var studyArea: Table users/retinta/tutorials/CaseStudy1

1 ////////////////////////////////////////////////// MTDD ALGORITHM //////////////////////////////////////
2 ////////////////////////////////////////////////// Sampling //////////////////////////////////////
3 // Outputs a user-defined number (90% of which are for training and 10% for validation) //
4 // of Intact Forest, Degraded Forest, and Deforested sampling points. If the output has //
5 // less points than expected, it is because the code ensures that the training samples //
6 // are uncorrelated with the validation samples by removing samples that are within some //
7 // distance to any other sample(s) //////////////////////////////////////////////////
8 // Based on Wang et al. (2019) and adapted by Raygadas et al. 2021 to the Southwestern //
9 // Amazon to detect intact, disturbed, and deforested areas/////////////////////////////////
10
11 ////////////////////////////////////////////////// User-defined Information //////////////////////////////////////
12
13 // Defines the study period
14 var startYear = 2000;
15 var endYear = 2018;
16
17 // Defines the number of desired sampling points per class:
18 // Intact forest, degraded forest, and deforested
19 // (90% will be used for training and 10% for validation)
20 var n = 500;
21
22 // Defines the study area
23 var aoi = studyArea;
24
25 // Defines the datasets to build conditional to detect intact, degraded, and deforested areas
26 var gfw = gfw; // Global Forest Watch (GFW)
27 var usgs = USGS_TC; // Global Forest Cover Change (GFCC) Tree Cover Multi-Year Global 30m
28 var mapbiomas = MAPBIOMAS; // Annual Land Cover, MapBiomas
29 var raisg = RAISG; // Deforestation, RAISG
30
31 // Defines a and b (see table in section 3.3.1 of the tutorial) tree cover thresholds
32 var tcMaxThres = 75;
33 var tcMinThres = 30;
34
35 // Defines a desired name that will be added to identifiers (eg. validationPts_"outputName")
36 var outputName = "MTDD";
37
```

Nota: Alguns dos conjuntos de dados usados para construir as condições datam de 2018.

Portanto, o período de estudo tem que cair entre 2000 e 2018.

Executando o Código

Execute o código clicando em run. Uma vez terminado, vá até o console de tarefas e clique em run para exportar os resultados como um raster.

```

CTD0_Sampling
87 ##### All conditions #####
88
89 ##### Deforested at some point / not deforested (RAISG) #####
90 var startYear = RAISG.starts.in 2001, this conditional selects 2001 as startYear if the actual startYear is lower (2000)
91 if (startYear < 2001) {startYear = 2001} else {startYear = startYear}
92 var def = raisg.lte(endYear).and(raisg.gte(startYear)) // Deforestation appears as 1
93 var noDef = def.not() // No deforestation appears as 1
94
95 ##### Forest loss at any time / no loss (GFW) #####
96 var endYear = endYear-2000 // converts the end year to a number of two digits
97 var startYear = startYear-2000 // converts the start year to a number of two digits
98 var loss = gfw.select("lossyear").lte(endYear).and(gfw.select("lossyear").gte(startYear)).rename();
99 var noLoss = loss.not()
100
101 ##### Tree cover greater than 75% in 2000 (GFW) #####
102 var tc75_2000 = gfw.select("treecover2000").gt(tcMaxThres);
103
104 ##### Tree cover criteria (USGS) #####
105 // The USGS dataset has TC data for 2005, 2010, and 2015, so it sets a conditional
106 // to select the TC dataset closest to the endYear
107 var tcYear;
108 if (endYear < 2007) {tcYear = 2005} // this conditional helps to select the TC dataset closest to the endYear
109 else if (endYear >= 2006 && endYear <= 2011) {tcYear = 2010};
110 else if (endYear > 2011) {tcYear = 2015};
111 // function for applying a filter to reduce noise in the TC USGS outputs (years 2000 and 2010 are specially noisy)
112 var filter = function (image) {
113   // Applies a 300 x 300 filter (default radius)
114   var imageFiltered = image.focal_mean();
115   // This is only for visualization purposes. The reproject is sufficient to force the computation to occur at native scale.
116   return imageFiltered.reproject("EPSG:4326", null, 10);
117 }
118
119 ##### Tree cover greater than 75% in 2015 or around the end of the study period (USGS)
120 var tc75_endYear = ugs.filterBounds(aoi).select("tree_cover_cover")
121   .filterMetadata("year", "equals", tcYear).mean().gt(tcMaxThres); // mean is only to convert it
122 var tc75_endYear_f11 = filter(tc75_endYear);
123
124 ##### Tree cover greater or equal than 10% and lower or equal than 75% in 2015 or around the end of the study period (USGS)
125 var tc10_endYear = ugs.filterBounds(aoi).select("tree_cover_cover")
126   .filterMetadata("year", "equals", tcYear).mean().gte(tcMinThres); // mean is only to convert it into a single image rather than image collection with only one
127 var tc10_75_endYear = ugs.filterBounds(aoi).select("tree_cover_cover")
128   .filterMetadata("year", "equals", tcYear).mean().lte(tcMaxThres);
129 var tc10_75_endYear = tc10_endYear.and(tc10_75_endYear);
130 var tc10_75_endYear_f11 = filter(tc10_75_endYear);
131
132 ##### Forest cover during all the study period (Mapbox) #####
133 var rename = function (image) { // function for assigning the same name to all bands
134   return image.select(0).rename("b1");
135 }
136 var mapbox_max_rv = mapbox_max_rv.rename(rename);
137 var mapbox_max_f11 = mapbox_max_rv.filter(mf.filter.and(created an collection containing the years within the study period (until 2019)
138   on filter.gte("year", startYear),
139   on filter.lte("year", endYear)));
140 var mapbox_max_minMax = mapbox_max_f11.reduce(mv.reduce.minMax()).rename("min", "max");
141 var mapbox_max_range = mapbox_max_minMax.expression("${min}" - "${max}").rename("range");
142 var forestAll = mapbox_max_minMax.select("max").lte(0.75/255).or(storage.googleapis.com/mapbox-public/RAISG/COLIM02/LIENDA/indice_de_la Leyenda_coleccion-1.pdf
143   .and(mapbox_max_range.gte(0)).rename("allForest")); // forest is 1 or 0 in the entire area-ecology region during 11 years
144
145 ##### Forest / non-forest at the end of the study period (Mapbox) #####
146 var forestEndYear = mapbox_max_rv.filter(mf.filter.and("year", endYear)).mean().lte(0.75/255); // mean is only to convert it into a single image rather than image collection with only one
147 var noForestEndYear = forestEndYear.not();
148
149 ##### Selection of Intact, disturbed, and deforested based on the above criteria #####
150
151 ##### Intact Forest (1)
152 // (Criteria) never classified as Deforested, TC>75% in 2000,
153 // no forest loss, TC>75% in 2015 (or around the end of the study period), classified as forest during all the study period)
154 var IntactForest = noDef.and(tc75_2000).and(noLoss)
155   .and(tc75_endYear).and(forestAll).clip(aoi);
156
157 ##### Degraded Forest (2)
158 // (Criteria) Deforested at some point, TC>30% in 2015 (or around the end of the study period),
159 // and classified as forest at the end of the study period)
160 var degradedForest = def.and(tc30_75_endYear_f11)
161   .and(forestEndYear).reproject([0,1],[0,7]).clip(aoi);
162
163 ##### Deforested (3)
164 // (Criteria) classified as deforested at some point, forest loss at some point,
165 // and classified as non-forest at the end of the study period)
166 var deforested = def.and(loss)
167   .and(noForestEndYear).reproject([0,1],[0,7]).clip(aoi);
168
169 ##### Merges classes and adds the result to the map (Using Image.js to combine provokes an error in the sampling)
170 var IntactDegDef = IntactForest.and(degradedForest).and(deforested).reproject([1,1],[1,1]).rename("class");
171
172 Map.addLayer(IntactDegDef, {opacity:1, name:"class"}, "palette":["deforest","deforest","deforest"],"Intact, Disturbed, and Deforested");
173 Map.centerObject(aoi, 10);

```

```

124 ////////////////////////////////////////////////// Random Sampling //////////////////////////////////////////
125
126 // Creates a random sample based on the user-defined number of sampling points per class
127 var samplingPts = IntactDefStratifiedSample({
128   numPoints: 0, // points for pixel values different than 1 and 2
129   seed: 0,
130   classValues: [1,2,3], // pixel values to be sampled
131   classPoints: {samPoints,samPoints,samPoints}, // number of sample points for each of the above classes
132   scale: 30, // Landsat spatial resolution
133   geometries: true, // retains the spatial information of the sample points needed for a spatial join
134 });
135
136 // Partitions the sample into training and validation points
137 samplingPts = samplingPts.randomColumn(); // adds column of uniform random numbers in a column named 'random'
138 var split = 0.9; // roughly 90% training, 10% validation
139 var training = samplingPts.filter(ee.Filter.lt('random', split));
140 var validation = samplingPts.filter(ee.Filter.gt('random', split));
141
142 // Ensures that the training samples are uncorrelated with the validation samples
143 // by removing samples that are within some distance to any other sample(s)
144 var distFilter = ee.Filter.withinDistance({//spatial join
145   distance: 500,
146   leftField: '.geo',
147   rightField: '.geo',
148   maxError: 10
149 });
150 var join = ee.Join.inverted();
151 training = join.apply(training, validation, distFilter); // applies the join
152
153 ////////////////////////////////////////////////// Prints and exports the training and validation points //////////////////////////////////////////
154
155 //Prints the results and adds them to the map
156 print("Training points", training.size());
157 //print(training);
158 Map.addLayer(training, {}, "Training Points");
159
160 print("validation points", validation.size());
161 //print(validation);
162 Map.addLayer(validation, {}, "Validation Points");
163
164 // Export the results as GEE assets (used as inputs of the map classified into intact, degraded, and deforested)
165 Export.table.toAsset({collection: training,
166   description: "TrainingPoints_" + outputName,
167   assetId: "trainingPts_" + outputName
168 });
169
170 Export.table.toAsset({collection: validation,
171   description: "ValidationPoints_" + outputName,
172   assetId: "validationPts_" + outputName
173 });
174
175 ////////////////////////////////////////////////// Print "all done" //////////////////////////////////////////
176 print("all done");
177

```

Randomly selects the user-defined number of samples per class

Divides the sampling points into training (90%) and validation (10%) datasets

Removes any points closer than 500 meters of each other to ensure training samples are uncorrelated with validation samples


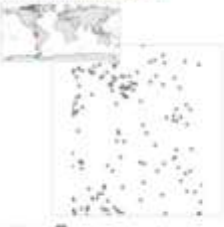
Prints the resulting number of training and validation points in the console and displays them in the map

Exports the results as GEE assets (used as inputs of the map classified into intact, degraded, and deforested)

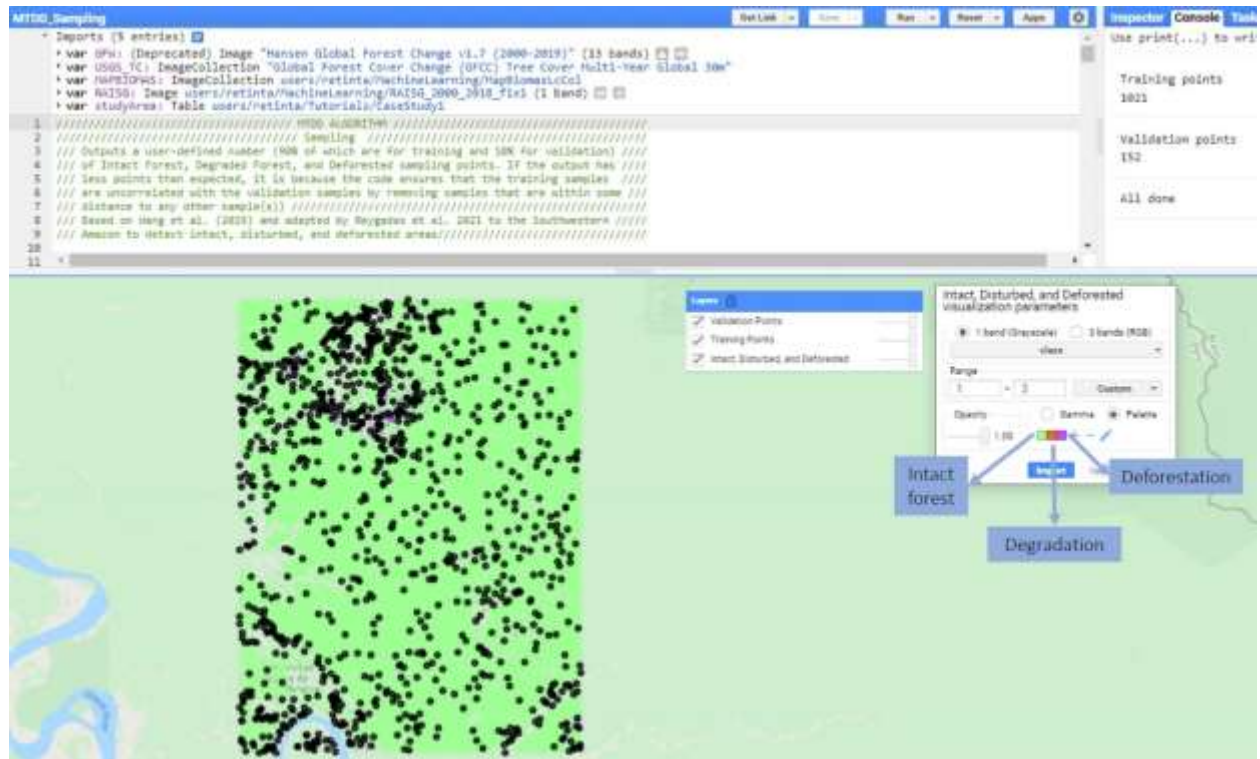
Saída

Este código produz dois conjuntos de dados: pontos de treinamento e pontos de validação.

GEE ativos

Table: trainingPts_MDTT	DESCRIPTION	FEATURES	PROPERTIES	Table: validationPts_MDTT	DESCRIPTION	FEATURES	PROPERTIES
	Feature Index	class (Long)	random (Float)		Feature Index	class (Long)	random (Float)
Table ID: users/rest/infra/tutorials/trainingPts_MDTT	0	1	0.5397274069840993	Table ID: users/rest/infra/tutorials/validationPts_MDTT	0	1	0.9287362220116006
	1	1	0.17310481412728573		1	1	0.9952952589520231
	2	1	0.3071274620055436		2	1	0.9668643293210513
	3	1	0.5262166033693878		3	1	0.9391284494480373
	4	1	0.06721850280471892		4	1	0.952914024892686

Mapa exibido em GEE



3.3.2. Mapa de degradação e desmatamento

Esta seção demonstra como executar este código para produzir um mapa classificado em floresta intacta, degradação e desmatamento.

Insumos

O usuário tem que inserir as seguintes entradas:

```
MTDD_ClassifiedMap
Imports (4 entries)
var mapBiomes: ImageCollection users/retinta/MachineLearning/MapBiomesCol
var tp: Table users/retinta/Tutorials/trainingPts_MDTT
var vp: Table users/retinta/Tutorials/validationPts_MDTT
var studyArea: Table users/retinta/Tutorials/CaseStudy1

1 /////////////////////////////////////////////////// MTDD ALGORITHM ///////////////////////////////////
2 /////////////////////////////////////////////////// Classification ///////////////////////////////////
3 // Outputs an image classified as Non Forest (0), Intact Forest (1), Disturbed Forest (2),
4 // and Deforestation (3), also VALIDATES the model and exports the results in csv format
5 ///////////////////////////////////////////////////
6 // Based on Wang et al. (2018) and adapted by Rodrigues et al. 2021 to the Southwestern
7 // Amazon to detect intact, disturbed, and deforested areas
8 ///////////////////////////////////////////////////
9
10 // Go to this link before starting: https://code.earthengine.google.com/?accept_repo=users/emaplab/public;
11 // If you want to display the map and print the accuracies in the console,
12 // you have to uncomment lines 270-273 & 307-308, but if the study area is big, it usually produces a time computation or memory limit error
13
14 /////////////////////////////////////////////////// User-defined information ///////////////////////////////////
15
16 // Defines the years of the training data (possible years: 2000-2018)
17 var startYearT = 2000;
18 var endYearT = 2018;
19
20 // Defines years for classification (possible years: 2000-present)
21 var startYearC = 2000;
22 var endYearC = 2020;
23
24 // Defines parameters to build a Landsat collection
25 var startDayS = '01-01';
26 var endDayS = '12-31';
27 var sds = studyArea;
28 var maskTheseS = ['cloud', 'shadow', 'snow', 'water'];
29
30 // Defines training and validation samples
31 var trainingPts = tp;
32 var validationPts = vp;
33
34 // Defines datasets to define forest and non forest areas
35 var mapBiomes = mapBiomes; // Annual Land Cover
36
37 // Defines an output name that will be added to these identifiers: MTDD_Classified
38 var outfile = '2018';
```

1. Training period: start and end year used to generate the training points (start and end year in the "MTDD_Sampling" GEE code)

2. Classification period: start and end year for the classification (may or may not coincide with the training period)

3. Parameters: to build an annual Landsat surface reflectance collection from which the time series are calculated

4. Training and validation points: the output from the "MTDD_Sampling" GEE code

5. Land-use and land-cover maps: used to define a forest mask

6. Output name: a desired name for the output map

Executando o Código

Execute o código clicando em run. Uma vez terminado, vá até o console de tarefas e clique em run para exportar os resultados como um arquivo raster (mapa classificado) e csv (matriz geral de precisão e erro).

```
40 //////////////////////////////////////////////////
41 // Function for calculating ALL METRICS //////////////////////////////////////////////////
42 var metricsEval = function (startYear, endYear, startDay, endDay, aoi, maskThese) {
43   ////////////////////////////////////////////////// Time Series Trajectories //////////////////////////////////////////////////
44   // Builds an annual cloud, cloud shadow, snow, and water masked mosaic composite of Landsat
45   // Surface Reflectance TM-equivalent bands 1(Blue), 2(Green), 3(Red), 4(NIR), 5(SWIR1640), 7(SWIR2130)
46   var ltgee = require('users/remaprlab/public/modules/LandTrendr.js'); // Requires the LandTrendr library
47   var annualSRC = ltgee.buildSRCcollection(startYear, endYear, startDay, endDay, aoi, maskThese);
48   // Function for converting original Surface Reflectance (16-bit signed integer) values to 0-1 range
49   // This is not a crucial step but will keep a more homogeneous range of values between indices(NDVI, NDWI, SAVI) and bands(B1 and B7)
50   var multiply = function (image) {
51     var multiplication = image.multiply(0.0001);
52     return multiplication.copyProperties(image, ['system:time_start']);
53   };
54   var annualSRC_md = annualSRC.map(multiply);
55   // Function for adding a time band that will be needed to calculate temporal metrics
56   var createTimeBand = function (image) {
57     // Scales milliseconds by a large constant to avoid very small slopes
58     // in the linear regression output (temporal metrics)
59     var time = image.metadata('system:time_start').divide(1e10).rename('time');
60     return image.addBands(time);
61   };
62   var annualSRC_md_tm = annualSRC_md.map(createTimeBand);
63   // Function for adding indices as new bands to each image in the collection
64   var addIndices = function (image) {
65     var ndvi = image.expression('(b(\''B4\'')-b(\''B3\''))/(b(\''B4\'')+b(\''B3\''))').rename('NDVI');
66     var ndwi1640 = image.expression('(b(\''B4\'')-b(\''B5\''))/(b(\''B4\'')+b(\''B5\''))').rename('NDWI1640');
67     var ndwi2130 = image.expression('(b(\''B4\'')-b(\''B7\''))/(b(\''B4\'')+b(\''B7\''))').rename('NDWI2130');
68     var sav = image.expression('(1.5*((b(\''B4\'')-b(\''B3\''))/(b(\''B4\'')+b(\''B3\''))+0.5))').rename('SAVI');
69     return image.addBands([ndvi, ndwi1640, ndwi2130, sav]);
70   };
71   var annualSRC_md_tm_indices = annualSRC_md_tm.map(addIndices);
72 }
```

Start of the function that calculates all 66 metrics.

Builds a collection with annual time series of Landsat TM-equivalent bands 1-5 & 7, NDVI, NDWI1, NDWI2, and SAVI

```

74 /////////////////////////////////////////////////// DESCRIPTIVE STATISTICS ///////////////////////////////////////////////////
75
76 // Location metrics: min, max, range, mean ////
77 var min = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
78   .reduce(ee.Reducer.min());
79 var max = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
80   .reduce(ee.Reducer.max());
81 var range = ee.Subtract(min).rename(['B5_range', 'B7_range', 'NDVI_range', 'NDVI2130_range', 'NDVI1640_range', 'SAVI_range']);
82 var mean = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
83   .reduce(ee.Reducer.mean());
84
85 // Scale metrics: stdDev, C.V., kurtosis, skewness ////
86 var stdDev = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
87   .reduce(ee.Reducer.stdDev());
88 var cv = mean.divide(stdDev).rename(['B5_cv', 'B7_cv', 'NDVI_cv', 'NDVI2130_cv', 'NDVI1640_cv', 'SAVI_cv']);
89 var kurt = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
90   .reduce(ee.Reducer.kurtosis());
91 var skew = annualSRC_md_tm_indices.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI'])
92   .reduce(ee.Reducer.skew());
93
94 // Temporal metrics ////
95 // Slope (output two bands: 'offset' (y-intercept) and 'scale' (slope))
96 var slopeB5 = annualSRC_md_tm_indices.select(['time', 'B5'])
97   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('B5_slope'));
98 var slopeB7 = annualSRC_md_tm_indices.select(['time', 'B7'])
99   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('B7_slope'));
100 var slopeNDVI = annualSRC_md_tm_indices.select(['time', 'NDVI'])
101   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('NDVI_slope'));
102 var slopeNDVI2130 = annualSRC_md_tm_indices.select(['time', 'NDVI2130'])
103   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('NDVI2130_slope'));
104 var slopeNDVI1640 = annualSRC_md_tm_indices.select(['time', 'NDVI1640'])
105   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('NDVI1640_slope'));
106 var slopeSAVI = annualSRC_md_tm_indices.select(['time', 'SAVI'])
107   .reduce(ee.Reducer.linearFit()).select(['scale'], rename('SAVI_slope'));
108
109 // Max-slope (maximum absolute linear regression slope of 5-year windows)
110 // Creates a moving 5-year window
111 var join = ee.Join.saveAll(['Returns a join that pairs each element from the annual SR collection
112 matchesKey: 'images' //with a group of matching elements from the 5-year window collection.
113 //The list of matches is added to each result as an additional property
114 //Establishes the 5-year filter
115 difference: 7800000000, // 2.5 years in milliseconds, the filter selects 2 years before and after the target year
116 leftField: 'systemtime_start', // therefore, the extreme windows are made of only 3-4 years
117 rightField: 'systemtime_start'
118 ]);
119 var fiveWindowJoin = join.apply(['Collection in which each image is associated with the 5-year window images (see proper lex:
120 primary: annualSRC_md_tm_indices,
121 secondary: annualSRC_md_tm_indices,
122 condition: diffFilter
123 ]);
124 // Function for calculating the absolute maximum slope over 5-year moving windows
125 var maxAbsMovSlope = function (invar, outvar) {
126 // Calculates slopes over 5-year windows
127 var m5Sip = ee.ImageCollection(fiveWindowJoin.map(function(image) {
128 var annualSRC_md_tm_indices = ee.ImageCollection.fromImages(image.get('images'));
129 return ee.Image(image).addBands(annualSRC_md_tm_indices.select(['time', invar])
130 .reduce(ee.Reducer.linearFit()));
131 }));
132 // Gets rid of the extreme windows, which are made of only 3 or 4 years
133 var range1 = m5Sip.reduceColumns(ee.Reducer.minMax(), ['systemtime_start']); //Gets the data range of images in the collection
134 var filter1 = m5Sip.filter(ee.Filter.date(range1.get('min')).not());
135 var filter2 = filter1.filter(ee.Filter.date(range1.get('max')).not());
136 var range2 = filter2.reduceColumns(ee.Reducer.minMax(), ['systemtime_start']);
137 var filter3 = filter2.filter(ee.Filter.date(range2.get('min')).not());
138 var filter4 = filter3.filter(ee.Filter.date(range2.get('max')).not()); // Print this to see all 5-yr window slopes
139 // Converts slope values to absolute numbers
140 var abs = function (image) {return image.select('scale').abs();}
141 // Extracts the maximum absolute slope
142 return filter4.map(abs).reduce(ee.Reducer.max()).rename(outvar);
143 }
144 // Applies the absolute moving slope function to all variables
145 var m5SipB5 = maxAbsMovSlope('B5', 'B5_m5Sip');
146 var m5SipB7 = maxAbsMovSlope('B7', 'B7_m5Sip');
147 var m5SipNDVI = maxAbsMovSlope('NDVI', 'NDVI_m5Sip');
148 var m5SipNDVI2130 = maxAbsMovSlope('NDVI2130', 'NDVI2130_m5Sip');
149 var m5SipNDVI1640 = maxAbsMovSlope('NDVI1640', 'NDVI1640_m5Sip');
150 var m5SipSAVI = maxAbsMovSlope('SAVI', 'SAVI_m5Sip');
151
152 //Value at last year
153 var rangeDates = annualSRC_md_tm_indices.reduceColumns(ee.Reducer.minMax(), ['systemtime_start']);
154 var lastYearFil = annualSRC_md_tm_indices.filter(ee.Filter.date(rangeDates.get('max')));
155 var lastYear = lastYearFil.select(['B5', 'B7', 'NDVI', 'NDVI2130', 'NDVI1640', 'SAVI']).toBands();
156 var lastYearVal = lastYear.rename(['B5_last', 'B7_last', 'NDVI_last', 'NDVI2130_last', 'NDVI1640_last', 'SAVI_last']);
157
158 // All metrics ////
159 // Creates a collection from all metrics
160 var metricsCollection = ee.ImageCollection([min, max, range, mean, stdDev, cv, kurt, skew,
161 slopeB5, slopeB7, slopeNDVI, slopeNDVI2130, slopeNDVI1640, slopeSAVI,
162 m5SipB5, m5SipB7, m5SipNDVI, m5SipNDVI2130, m5SipNDVI1640, m5SipSAVI, lastYearVal]);
163
164 // Converts the metrics collection to a single multi-band image
165 var metrics = metricsCollection.toBands();
166 return metrics;
167 }
168 ///////////////////////////////////////////////////

```

Calculates 11 descriptive statistics (i.e., minimum, maximum, range, mean, standard deviation, coefficient of variation, kurtosis, skewness slope, maximum 5-year slope, and most recent value) for each of the 6 time series (i.e., NDVI, two SWIR spectral regions, two NDWI indices, and SAVI)

End of the function that calculates all 66 metrics

```

173 ////////////////////////////////////////////////// Masking: delimitation of forested areas ///////////////////////////////////
174
175 // Selects areas that were forest at least 3 consecutive years during the study period//
176 var rename = function (image) { // Function for assigning the same name to all bands
177   return image.select(0).rename("b1");
178 }
179 var mapBiomass_r = mapBiomass.map(rename);
180 var mapBiomass_fil = mapBiomass_r.Filter(ee.Filter.and([ //Creates an collection containing the years within the study period (until 2018)
181   ee.Filter.gte('year', startYearT),
182   ee.Filter.lte('year', endYearT)]));
183 // Function for detecting pixels covered by forest
184 //https://storage.googleapis.com/mapbiomas-public/BAI5B/COLECA02/LPDHDA/codigo_de_la_leyenda_coleccion-2.pdf
185 //forest is 3 or 8 in the entire Acre-Ucayali region during all years
186 var forest = function (image) {
187   return image.eq(3).or(image.eq(8)).rename("forest").copyProperties(image, ['year']);
188 }
189 var forestCol = mapBiomass.map(forest);
190
191 // Function for adding a time band that will be needed to calculate land covers per year
192 var createTimeBandMask = function (image) {
193   var time = image.metadata('year').rename('time');
194   return image.addBands(time);
195 };
196 var forestCol_tm = forestCol.map(createTimeBandMask);
197
198 // Forest in three consecutive years
199 // Creates a moving 3-year window
200 var join1 = ee.Join.saveAll([matchesKey: 'images']);
201 var diffFilter1 = ee.Filter.maxDifference({difference: 1.5, leftField: 'year', rightField: 'year'});
202 var threeWindowJoin = join1.apply([primary: forestCol_tm, secondary: forestCol_tm, condition: diffFilter1]);
203
204 // Function for detecting forest cover over 3-year moving windows
205 var forest3years = function (invar, outvar) {
206   // Calculates sum over 3-year windows
207   var f3y = ee.ImageCollection(threeWindowJoin.map(function (image) {
208     var forestCol_tm = ee.ImageCollection.fromImages(image.get('images'));
209     return ee.Image(image).addBands(forestCol_tm.select(['time', invar])
210       .reduce(ee.Reducer.sum())));
211   }));
212   // Extracts the maximum sum
213   return f3y.reduce(ee.Reducer.max());
214 };
215
216 // Applies the "detecting forest cover over 3-year" function to forest presence per year
217 var MaxForest3years = forest3years('forest', 'forest_3years').select('forest_sum_max');
218 // Gets the Forest mask (areas that were forest at least three consecutive years)
219 var forestMask = MaxForest3years.gte(3);
220

```

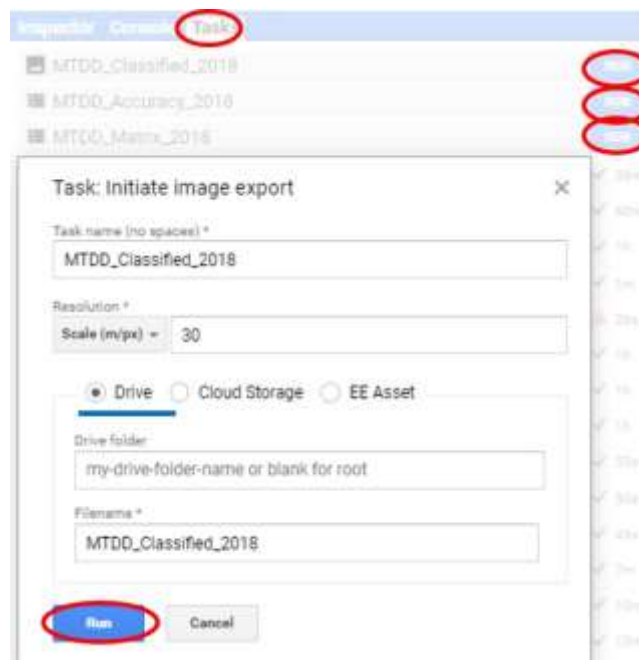
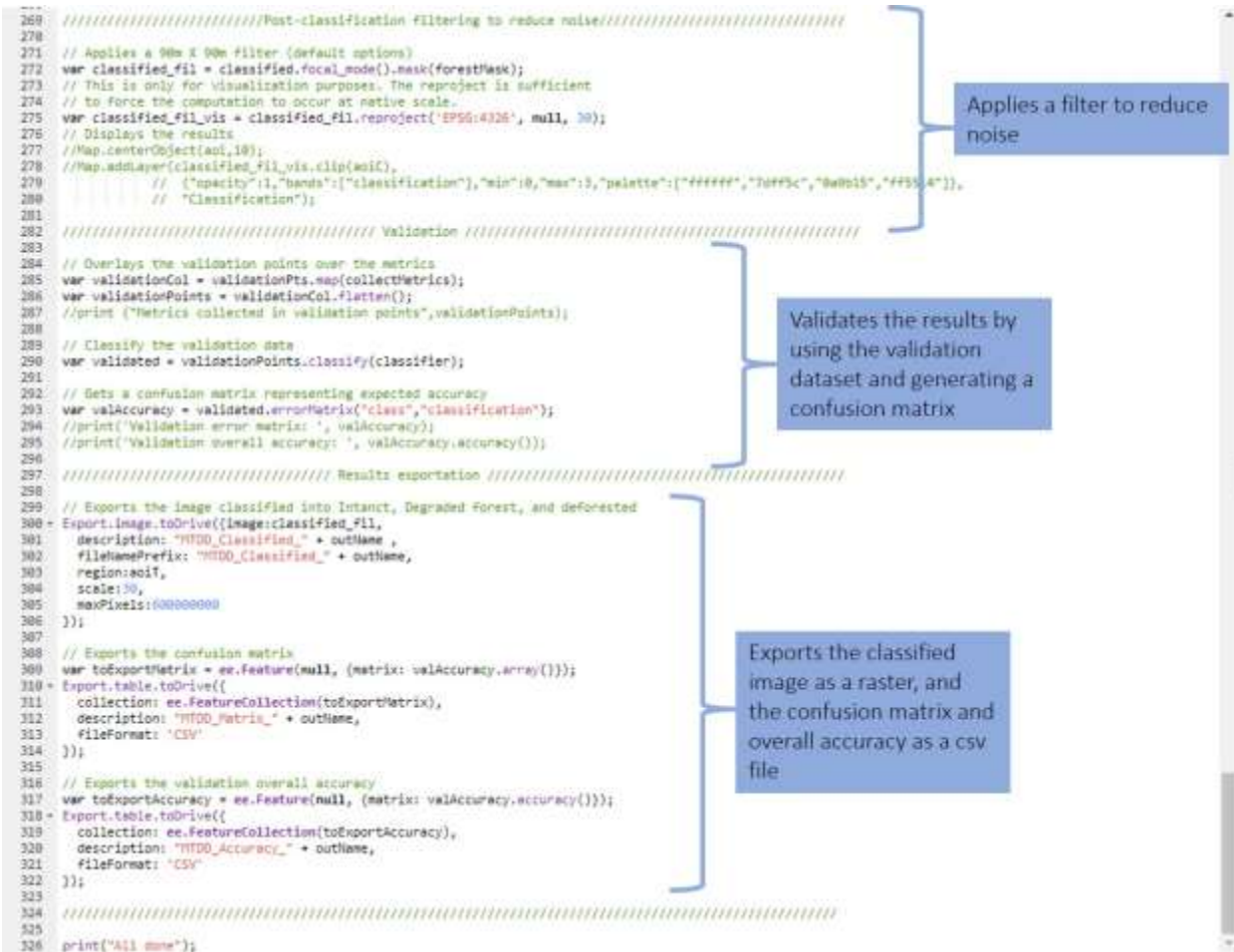
Creates a forest mask composed of all areas that were forest at least three consecutive years during the study period

```

218 ////////////////////////////////////////////////// Clasificador random forest ///////////////////////////////////
219
220 // *Crea una colección con todas las métricas con base en los años del muestreo
221 var metricsTraining = metricsGral(startYearT, endYearT, startDayB, endDayB, aoiB, maskTheseB);
222 print("Métricas muestreo", metricsTraining);
223
224 // **Crea una colección con todas las métricas con base en los años para la clasificación
225 var metricsClassification = metricsGral(startYearC, endYearC, startDayB, endDayB, aoiB, maskTheseB);
226 print("Métricas clasificación", metricsClassification);
227
228 // Sobreponen los puntos de entrenamiento con las métricas
229 var collectMetrics = function (feature) { // usar una función permite a GEE trabajar con más puntos antes de exceder su capacidad
230   return metricsTraining.sampleRegions({collection: feature,
231     properties: ['class'],
232     scale: 30,
233     tileScale: 2});
234 };
235 var trainingCol = trainingPts.map(collectMetrics);
236 var trainingPoints = trainingCol.flatten();
237
238 // Crea un clasificador random forest con 500 árboles y lo entrena
239 var classifier = ee.Classifier.smileRandomForest({numberOfTrees: 500})
240   .train({features: trainingPoints, classProperty: 'class',
241     inputProperties: ['0_B5_min', '0_B7_min', '0_HMVI_min', '0_NDMI1130_min', '0_NDMI1640_min', '0_SAVI_min',
242       '1_B5_max', '1_B7_max', '1_HMVI_max', '1_NDMI1130_max', '1_NDMI1640_max', '1_SAVI_max',
243       '2_B5_range', '2_B7_range', '2_HMVI_range', '2_NDMI1130_range', '2_NDMI1640_range', '2_SAVI_range',
244       '3_B5_mean', '3_B7_mean', '3_HMVI_mean', '3_NDMI1130_mean', '3_NDMI1640_mean', '3_SAVI_mean',
245       '4_B5_stdDev', '4_B7_stdDev', '4_HMVI_stdDev', '4_NDMI1130_stdDev', '4_NDMI1640_stdDev', '4_SAVI_stdDev',
246       '5_B5_cv', '5_B7_cv', '5_HMVI_cv', '5_NDMI1130_cv', '5_NDMI1640_cv', '5_SAVI_cv',
247       '6_B5_kurtosis', '6_B7_kurtosis', '6_HMVI_kurtosis', '6_NDMI1130_kurtosis', '6_NDMI1640_kurtosis', '6_SAVI_kurtosis',
248       '7_B5_skew', '7_B7_skew', '7_HMVI_skew', '7_NDMI1130_skew', '7_NDMI1640_skew', '7_SAVI_skew',
249       '8_B5_slp', '8_B7_slp', '8_HMVI_slp', '8_NDMI1130_slp', '8_NDMI1640_slp', '8_SAVI_slp',
250       '9_B5_msdSlp', '9_B7_msdSlp', '9_HMVI_msdSlp', '9_NDMI1130_msdSlp', '9_NDMI1640_msdSlp', '9_SAVI_msdSlp',
251       '10_B5_last', '10_B7_last', '10_HMVI_last', '10_NDMI1130_last', '10_NDMI1640_last', '10_SAVI_last']});
252
253 // Clasifica las métricas deseadas
254 var metricsMask = metricsClassification.map(forestMask); // Mascarar las áreas no forestales
255 var classified = metricsMask.classify(classifier); // No bosque (0), bosque intacto (1), bosque degradado (2), áreas deforestadas (3)
256 print("Mapa clasificado");
257

```

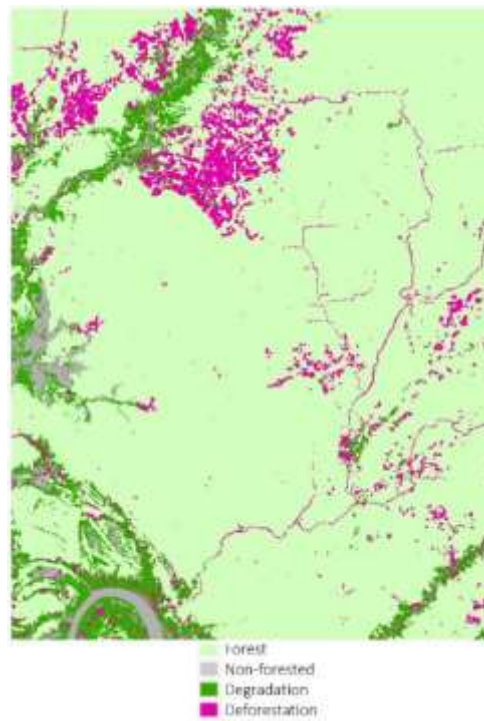
Entrena un clasificador random forest con las 66 métricas de los datos de entrenamiento y la clasifica las imágenes deseadas



Saída

Este código produz um mapa classificado em floresta não florestal, floresta intacta, degradação e desmatamento.

Raster (".tif" file)



Matriz geral de precisão e confusão (".csv" arquivos)

	A	B	C
1	system:in matrix	.geo	
2	0	0.927632	
3			

	A	B	C	D	E	F
1	system:in	matrix	.geo			
2	0	[[0, 0, 0, 0], [0, 60, 0, 0], [0, 0, 47, 4], [0, 1, 6, 34]]				
3						
4						

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