

Tutorial for mapping forest disturbances across the Southwestern Amazon using CODED, LandTrendr, and MTDD

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Tutorial for mapping forest disturbances across the Southwestern Amazon using CODED, LandTrendr, and MTDD

1. Background

Due to the urgent need to understand the effects of forest disturbances on ecosystem services, multiple remote sensing algorithms focused on detecting vegetation changes have been developed in the last decade. The challenge now lies in understanding which algorithm best suits the user's study area and research objective. This tutorial shares our Google Earth Engine (GEE) work derived from the evaluation of the performance of three algorithms—Continuous Degradation Detection (CODED), Landsat-based detection of trends in disturbance and recovery (LandTrendr), and Multi-variate Time-series Disturbance Detection (MTDD)—to detect and characterize forest disturbances in the Southwestern Amazon (SWA). For the entire study, please refer to Reygadas et al. (2021) (currently under review).

In section 3.3, we share MTDD-based GEE codes to map disturbances in the SWA (i.e., Ucayali, Peru and Acre, Brazil). Complete GEE tutorials for [CODED](#) and [LandTrendr](#) are freely available online; in this tutorial, we share the specific configuration-parametrization for the SWA.

2. Definitions

Although it is hard to adopt a set of definitions that harmonize with the fundamental logic behind each algorithm, we refer to deforestation, forest degradation, and forest disturbances as follows:

- **Deforestation.** Long-term or permanent conversion of forested land to non-forested land (FAO, 2001).
- **Forest degradation.** While there is not a widely accepted definition, it is generally considered a long-term process that does not lead to a land cover change but negatively affects the forest's structure and function (Sasaki and Putz, 2009; Schoene et al., 2007).
- **Forest disturbances.** Drivers of forest's state and function that can vary from high-impact events, such as fires or deforestation, to subtle and gradual processes, such as those caused by prolonged droughts, insects, or diseases (Cohen et al., 2017; McDowell et al., 2015).

Accordingly, we consider both deforestation (i.e., high-impact event) and forest degradation (i.e., subtle and gradual process) types of forest disturbances.

3. Algorithms

All three algorithms use surface reflectance values of Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper+ (ETM+), and Landsat Operational Land Imager (OLI).

3.1. CODED

CODED v0 uses time series of endmember fractions and NDFI to detect and characterize disturbances which can later be classified as degradation or deforestation. See Bullock et al. (2020) for algorithm details and Bullock (2020) for GEE implementation.

3.1.1. Disturbances map

This section demonstrates how to run this [code](#) to produce a forest disturbance map.

Inputs

The user has to enter the following inputs:

```
CODED_DisturbancesMap
  ▾ 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 Y. 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   'cfThreshold': .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': [500, 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';
```

1. Study Area: polygon of the study area.

2. Training data: CODED requires the user to collect land-cover and land-use samples from a selected training period within the entire study period. This is usually obtained through a stratified random sample based on a combination of land-use and land-cover maps and high spatial resolution imagery available in GEE. The field that contains the land-cover identifiers must be named "label".

3. Set of parameters

4. Output name: a desired name for the disturbances map.

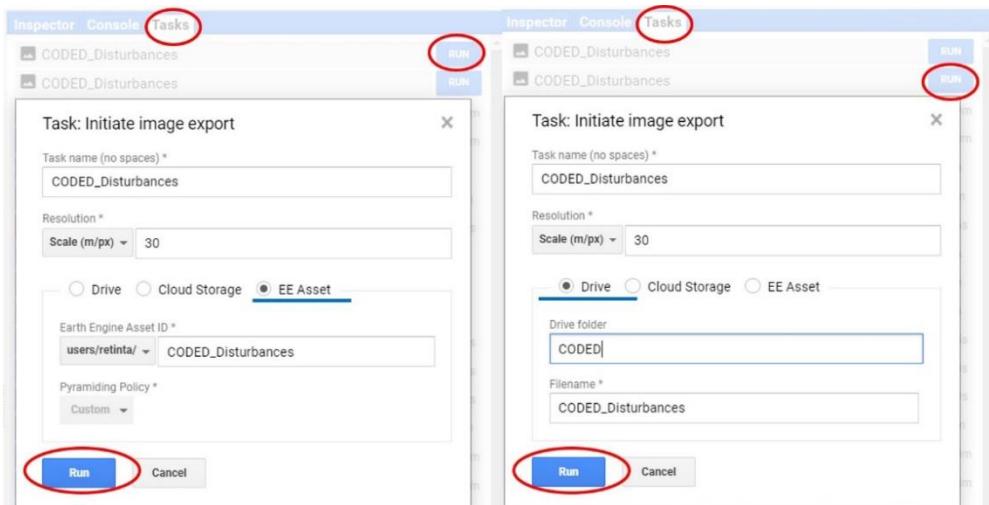
Running the code

Execute the code by clicking run. Once it is all done, go to the task console and click run to export the results as a GEE asset and as a raster.

```

CODED_DisturbancesMap
-- 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: 1e13,
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");

```



Output

This code outputs a disturbance map with four layers per disturbance (i.e., date of occurrence, magnitude of change, post-disturbance land-cover, NDFI difference from before and after the disturbance) and one last layer indicating the land-cover type in the start year.

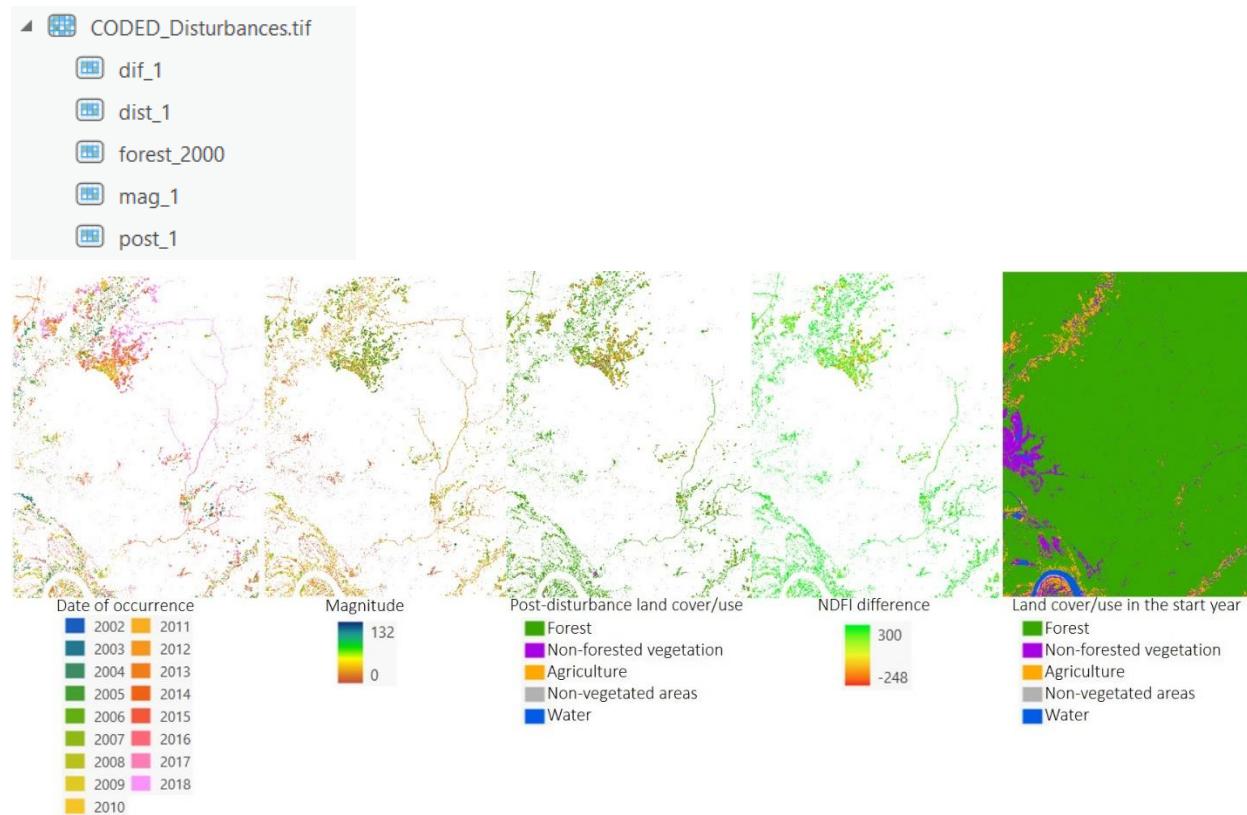
GEE asset

Image: CODED_Disturbances

Index	Name	Type	Dimensions	CRS	Nominal Scale	Min	Max
0	dist_1	signed int16	981x1287 px	EPSG:4326	30.00000000000004	2002	2018
1	mag_1	signed int16	981x1287 px	EPSG:4326	30.00000000000004	3	132
2	post_1	signed int16	981x1287 px	EPSG:4326	30.00000000000004	0	5
3	dif_1	signed int16	981x1287 px	EPSG:4326	30.00000000000004	-248	300
4	forest_2000	signed int16	981x1287 px	EPSG:4326	30.00000000000004	1	5

Image ID: users/retinta/Tutorials/CODED_Disturbances

Raster (.tif" file)



3.1.2. Degradation and deforestation map

This section demonstrates how to run this [code](#) to produce a map classified into forest, non-forest, degradation, and deforestation.

Inputs

There are three inputs the user has to enter:

```
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 Y. Reygadas and V. Galati ///////////
5
6 //////////////// User-defined information ///////////
7 // Defines the study area
8 var studyArea = stArea; 1. Study Area: polygon of the study area.
9
10 // Specifies the disturbances map to be stratified
11 var dist_map = distMap; 2. Disturbances map: the output from the "CODED_DisturbancesMap" GEE code
12
13 // Defines the output name for the stratified map
14 var outName = 'CODED_DegDef'; 3. Output name: a desired name for the degradation and deforestation map.
15
16
17
```

Running the code

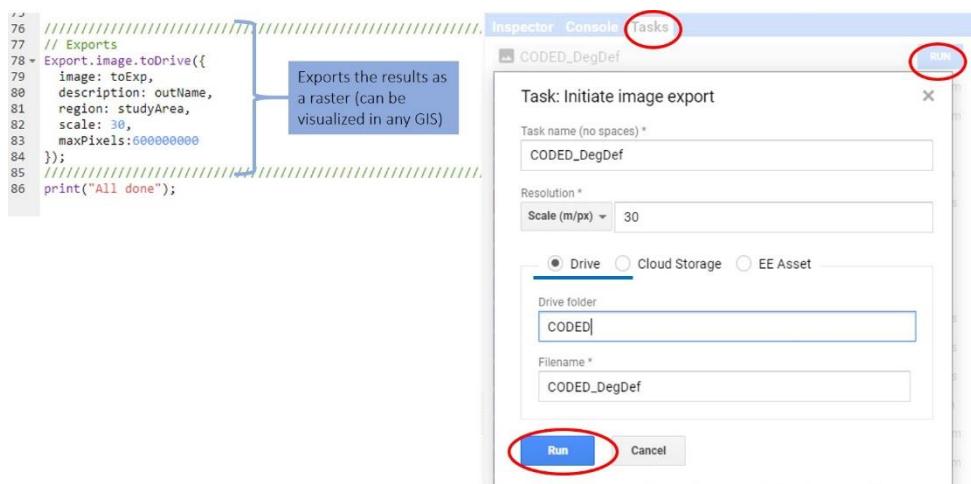
Execute the code by clicking run. Once it is all done, go to the task console and click run to export the results as a raster.

```

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 not disturbances, then nonForest and relabel
32   var nonForested = unmasked.select('forest_2000').neq(1)
33     .and(unmasked.select('dist_1').eq(0)).remap([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     .remap([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     .remap([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', '#5CE5D5','#FF2079'];
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

```

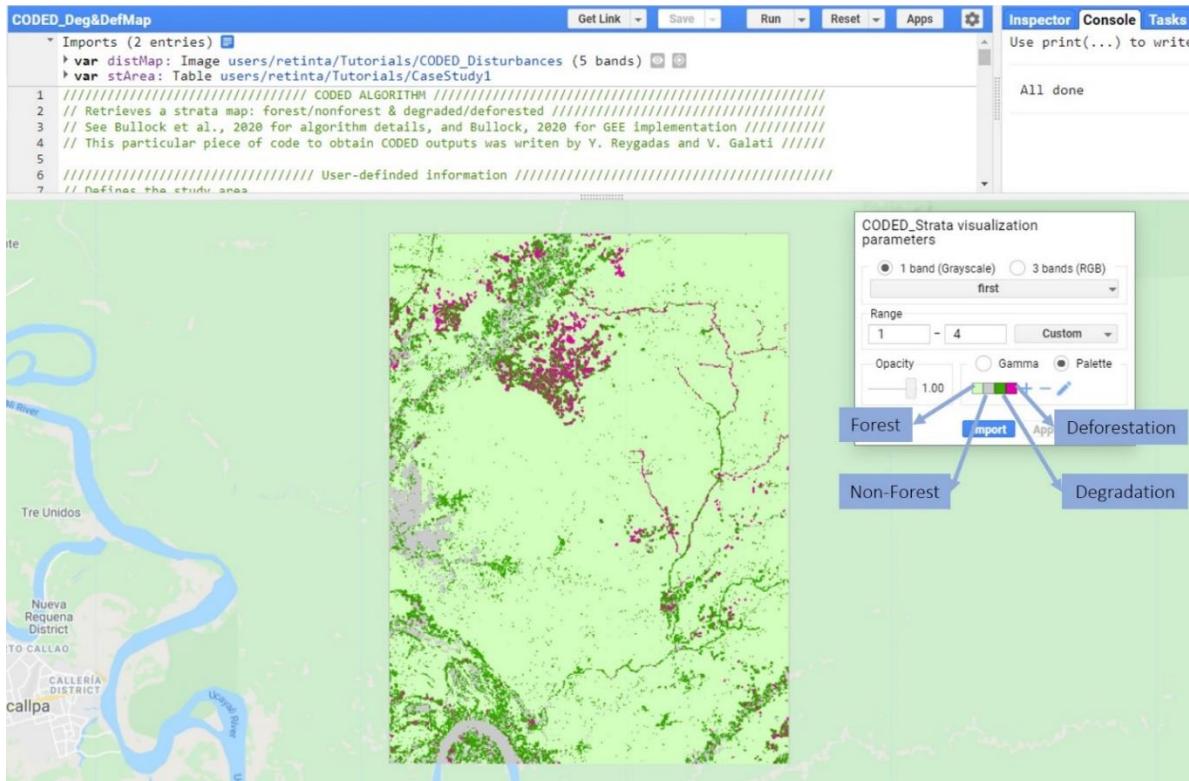
Produces and displays a map classified into forest, non-forest, degradation, and deforestation based on the conditions described in green



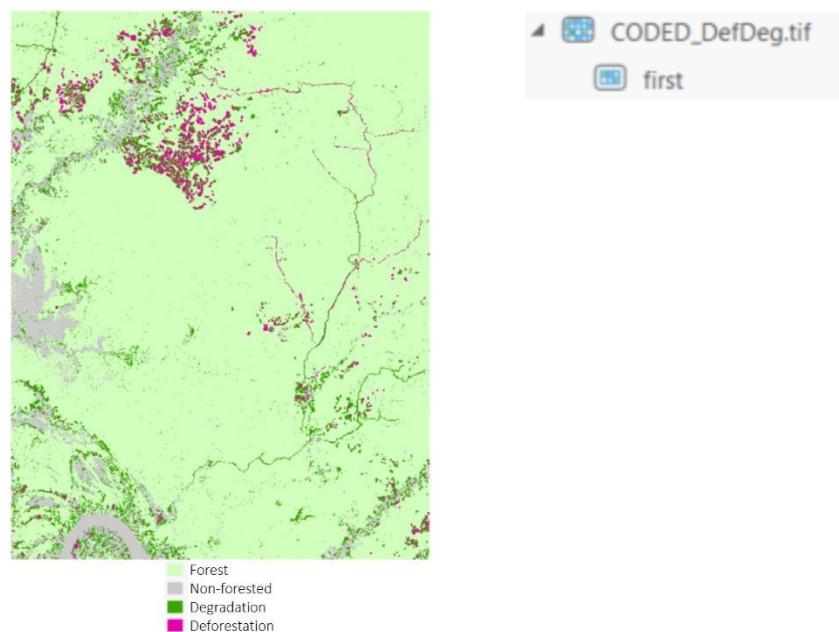
Output

This code outputs a map classified into forest, non-forest, degradation, and deforestation.

Map displayed in GEE



Raster ("tif" file)



3.2. LandTrendr

LandTrendr detects and characterizes vegetation loss or gain by segmenting and fitting temporal trajectories of a user-defined variable (possible input variables: NDFI*added, NBR, NDVI, NDSI, NDMI, TCB, TCG, TCW, TCA, and Landsat TM-equivalent bands 1-5 and 7). See Kennedy et al. (2010) for algorithm details and Kennedy et al. (2018) for GEE implementation.

3.2.1. Disturbances map

This section demonstrates how to run this [code](#) to produce a forest disturbance map.

Inputs

The user has to enter the following inputs:

```
LT_DisturbancesMap
  * Imports (1 entry)
    > var studyArea: Table users/retinta/Tutorials/CaseStudy1
    // LANDTRENDR ALGORITHM
    // Retrieves annual and multiyear disturbance maps based on specified paramenters
    // See Kennedy et al., 2010 for algorithm details, and Kennedy et al., 2018 for GEE implementation
    // This particular piece of code to obtain LandTrendr outputs was written by Y. Reygadas and V. Galati //
    // User-defined information
    // Defines the input variable (s)
    var indices = ['NDFI']; // Input variable(s) to be segmented
    // Defines collection parameters
    var startYear = 2000; // The minimum year in the desired range of annual collection
    var endYear = 2018; // The maximum year in the desired range of annual collection
    var startDay = '01-01'; // The maximum date in the desired seasonal range over which to generate annual composite
    var endDay = '12-31'; // The minimum date in the desired seasonal range over which to generate annual composite
    var aoi = studyArea; // The study area over which to mosaic images
    var maskThese = ['cloud', 'shadow', 'snow', 'water']; //A list of CFMASK mask classes to include as masked pixels
    // Defines landtrendr parameters
    var runParams = {
      maxSegments: 6, // Maximum number of segments to be fitted on the time series
      spikeThreshold: 1, // Threshold for dampening (1 means no dampening)
      vertexCountOvershoot: 3, // The initial regression-based detection of potential vertices can overshoot the maxSegments+1 vertices by this value. Angle-based culling is used to return to the desired number of vertices if overshoot occurs. It allows a mix of criteria for vertex identification
      preventOneYearRecovery: false, // Prevent segments that represent one year recoveries
      recoveryThreshold: 0.05, // During fitting, if a segment has a recovery rate faster than 1/recoveryThreshold (in years), that segment is disallowed (1 turns off this parameter)
      pvalThreshold: 0.05, // If the p-value of the best fitted model exceeds this threshold, the model is discarded and another is fitted using the Levenburg-Marquardt approach
      bestModelProportion: 0.75, // Takes the model with most vertices that has a p-value that is at most this proportion away from the model with lowest p-value
      minObservationsNeeded: 3 // Minimum observations needed to perform output fitting
    };
    // Filters vegetation changes by:
    var changeParams = {
      delta: 'loss', // loss or gain
      sort: 'greatest', // type (greatest, least, newest, oldest, fastest, or slowest)
      year: {checked:true, start:startYear, end:endYear}, //period of time (in years)
      mag: {checked:true, value:150, operator:'>'}, // magnitude (if the input is a normalized index)
      dur: {checked:true, value:19, operator:'<'}, // duration (in years)
      preval: {checked:true, value:150, operator:'>'}, // pre-change spectral value (if the input is multiplied by 1000)
      mmu: {checked:true, value:3}, // minimum patch size (number of pixels)
    };
    // Define study area name (the output name will contain identifiers e.g., "LT_NDFI multivear", before the name you assign)
    var outName = "Disturbances";
    // Define output folder
    var outFolder = "LT";
```

1. Input variable(s) to be segmented and from which vegetation changes will be detected

2. Parameters to build an annual collection of Landsat surface reflectance from which input variable-time series are calculated

3. Parameters to control the segmentation of the input variable(s)

4. Parameters to filter vegetation changes (multiplied by 1000)

5. Output name and folder: a desired name for the disturbances map and the desired output folder in Google drive

Running the code

Execute the code by clicking run. Once it is all done, go to the task console and click run to export the results as a raster.

```
LT_DisturbancesMap
32
33 //////////////////////////////////////////////////////////////////
34 // Require the LandTrendR Library that has NDFI added
35 var ltgee = require('users/retinta/Tutorials:LT_Utility_NDFI');
36
37 //////////////////////////////////////////////////////////////////
38 // Function for running LandTrendR per index
39 var doLT = function(indices) {
40   for(var i in indices) {
41     // Add index to changeParams object
42     changeParams.index = indices[i];
43     // Run landtrendr
44     var LTrsult = ltgee.runLT(startYear, endYear, startDay, endDay, aoi, indices[i], [], runParams, maskThese);
45     // Call function for getting the disturbances map
46     combinedMap(LTrsult,indices[i]);
47   }
48 }
49
50 // Function for getting a disturbances map per index
51 var combinedMap = function(result,index) {
52   changeParams.year = {checked:true, start:startYear, end:endYear};
53   // Get the change map layers (yod, mag, dur, preval, rate, dsmr)
54   var changeImg = ltgee.getChangeMap(result, changeParams);
55   // Display the change attribute map (specifically year of disturbance-yor)
56   Map.addLayer(changeImg.select(['yod']).clip(aoi), yodVizParms, String(index));
57   //Export results
58   exportResults(changeImg,index,outName,outFolder);
59 }
60
61 // Function for exporting data
62 var exportResults = function(img, index, name,folder){
63   Export.image.toDrive({
64     image: img.clip(aoi).unmask(@).short(),
65     description: 'LT_'+String(index)+'_'+name,
66     folder: folder,
67     region: aoi,
68     scale: 30,
69     maxPixels: 10000000000000
70   });
71 }
72
73 //////////////////////////////////////////////////////////////////
74 // Visualization parameters (year of disturbance)
75 var palette = ['#9400D3', '#4B0082', '#0000FF', '#00FF00', '#FFFF00', '#FF7F00', '#FF0000'];
76 var yodVizParms = {
77   min: startYear,
78   max: endYear,
79   palette: palette
80 };
81
82 // Adjusts map
83 Map.centerObject(aoi,10);
84
85 // Runs everything ///
86 doLT(indices);
87 //////////////////////////////////////////////////////////////////
88 print("All done");
89
```

Requires the Landtrendr library that also supports NDFI

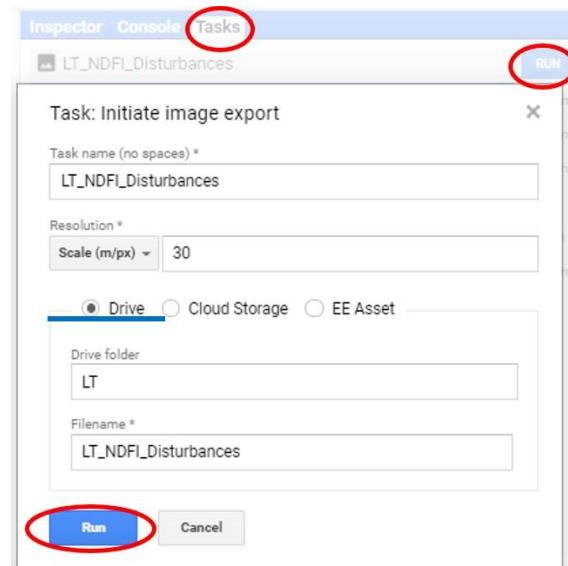
Segments the input variable(s)

Produces a disturbances map with the user-defined filtering criteria

Exports the results as raster(s)

Sets the map visualization parameters

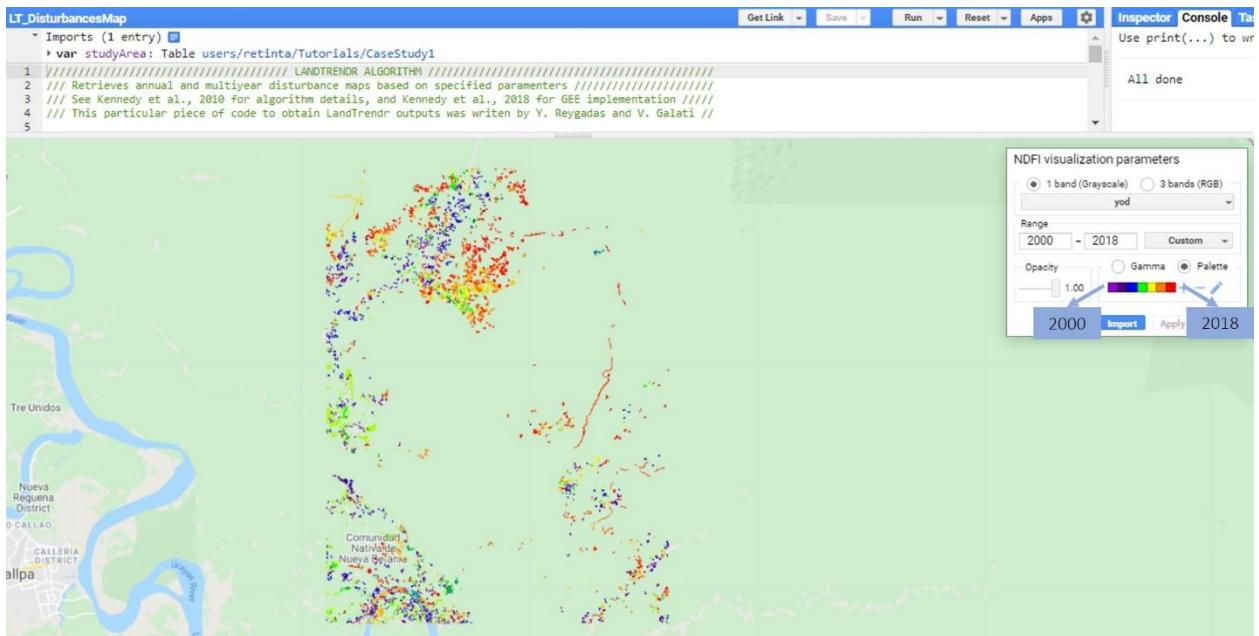
Runs all functions



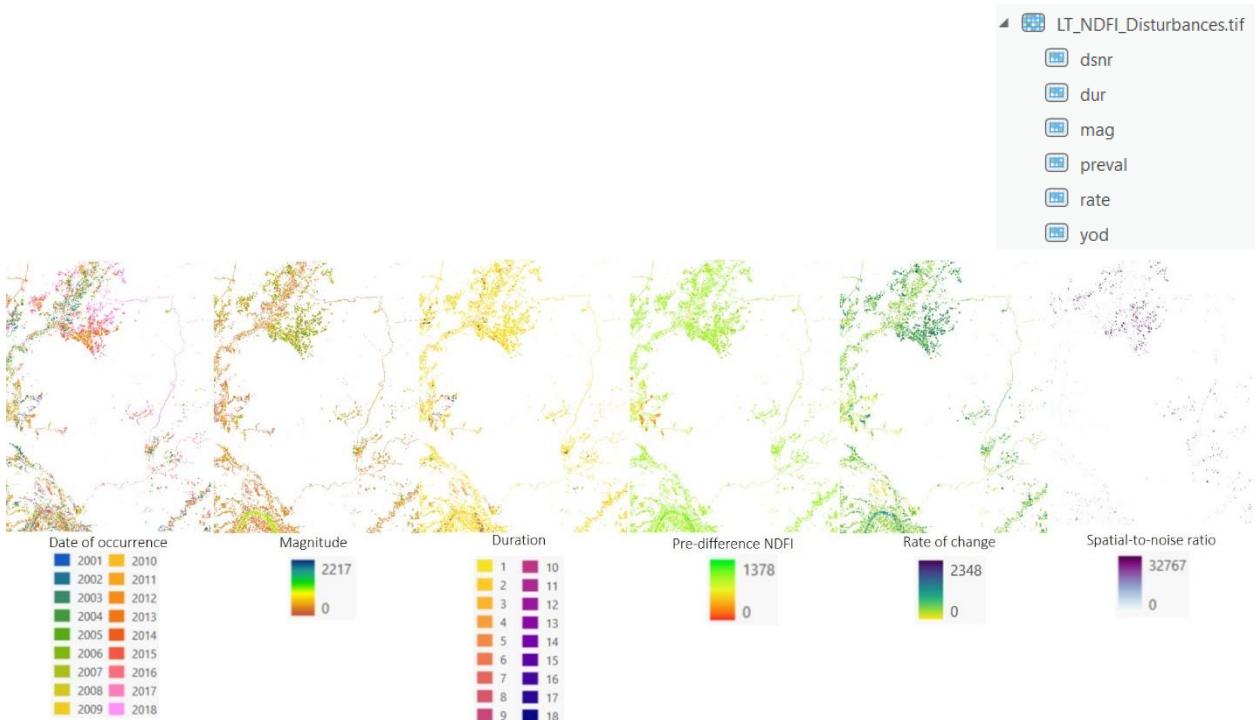
Output

This code outputs a disturbance map with six layers: date of occurrence, magnitude of change, duration, pre-change spectral value, rate of change, and signal-to-noise ratio.

Map displayed in GEE (only “year of disturbance” layer)



Raster (“.tif” file)



3.3. MTDD

This MTDD-based algorithm classifies initially forested areas into intact, degraded, and deforested by training a random forest model with sixty-six metrics derived from six annual time series (i.e., NDVI, two SWIR spectral regions, two NDWI indices, and SAVI) from which eleven descriptive statistics (i.e., minimum, maximum, range, mean, standard deviation, coefficient of variation, kurtosis, skewness, slope, maximum 5-year slope, and most recent value) are calculated. We built this MTDD GEE code based on Wang et al. (2019) and adapted it to the SWA.

3.3.1. *Training samples*

This section demonstrates how to run this [code](#) to produce samples which are later used to train a random forest classifier.

The samples are randomly selected from the following set of conditions:

Class	Condition	Reference dataset
Intact	Forest cover in the entire study period	MapBiomass (MapBiomass, 2020)
	No deforested in the entire study period	RAISG (RAISG, 2020)
	No forest loss in the entire study period	GFC (Hansen et al., 2013)
	Tree cover greater than 75% ^a in 2000	GFC (Hansen et al., 2013)
	Tree cover greater than 75% ^a in 2015	GFCC (Sexton et al., 2013)
Degraded	Forest cover in the end-year	MapBiomass (MapBiomass, 2020)
	Deforested at some point in the study period	RAISG (RAISG, 2020)
	Tree cover greater than 30% ^b and lower than 75% ^a in 2015	GFCC (Sexton et al., 2013)
Deforested	No forest cover in the end-year	MapBiomass (MapBiomass, 2020)
	Deforested at some point in the study period	RAISG (RAISG, 2020)
	Forest loss at some point in the study period	GFC (Hansen et al., 2013)

^a and ^b tree cover thresholds can be modified in the GEE code

Inputs

The user has to enter the following inputs:

```
MTDD_Sampling
* Imports (5 entries) 
  > var GFW: (Deprecated) Image "Hansen Global Forest Change v1.7 (2000-2019)" (13 bands) A 
  > var USGS_TC: ImageCollection "Global Forest Cover Change (GFCC) Tree Cover Multi-Year Global 30m"
  > var MAPBIOMAS: ImageCollection users/retinta/MachineLearning/MapBiomassLcCol
  > var RAISG: Image users/retinta/MachineLearning/RAISG_2000_2018_fix1 (1 band) C 
  > 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 other sample(s) ///////////////////////////////////////////////////////////////////
8 /// Based on Wang et al. (2019) and adapted by Reygadas et al. 2021 to the Southwestern ///
9 /// Amazon to detect intact, disturbed, and deforested areas///////////////////////////////////////////////////////////////////

10 ////////////////////////////////////////////////////////////////// User-defined information //////////////////////////////////////////////////////////////////
11
12 // Defines the study period
13 var startYear = 2000;
14 var endYear = 2018; 1. Study period: start and end year

15 // Defines the number of desired sampling points per class:
16 //intact forest, degraded forest, and deforested
17 // (90% will be used for training and 10% for validation)
18 var samPoints = 500; 2. Sampling points: number of desired sampling points per class

19 // Defines the study area
20 var aoi = studyArea; 3. Study Area: polygon of the study area

21 // Defines the datasets to build conditional to detect intact, degraded, and deforested areas
22 var gfw = GFW; // Global Forest Watch (GFC)
23 var usgs = USGS_TC; // Global Forest Cover Change (GFCC) Tree Cover Multi-Year Global 30m
24 var mapBiomass = MAPBIOMAS; // Annual Land Cover, MapBiomass
25 var raisg = RAISG; // Deforestation, RAISG 4. Reference datasets: sources to build the conditions

26 // Defines a and b (see table in section 3.3.1 of the tutorial) tree cover thresholds
27 var tcMaxThres = 75;
28 var tcMinThres = 30; 5. Three cover thresholds: desired tree cover threshold for some of the conditions (see table above)

29 // Defines a desired name that will be added to identifiers (e.g. validationPnts "outputName")
30 var outputName = "MTDT"; 6. Output name: desired name for the training and validation points

31
32
33
34
35
36
37
```

Note: Some of the datasets used to build the conditions date back to 2018. Therefore, the study period has to fall between 2000 and 2018.

Running the code

Execute the code by clicking run. Once it is all done, go to the task console and click run to export the results as a GEE asset.

```

MTDD_Sampling
  37 ////////////////////////////////////////////////////////////////// All conditions //////////////////////////////////////////////////////////////////
  38
  39 ////////////////////////////////////////////////////////////////// Deforested at some point / not deforested (RAISG) //////
  40 var rStartYear; // RAISG starts in 2001, this conditional selects 2001 as startYear if the actual startYear is lower (2000)
  41 if (startYear < 2001) {rStartYear = 2001;} else {rStartYear = startYear}
  42 var def = raisg.lte(endYear).and(raisg.gte(rStartYear));//Deforestation appears as 1
  43 var noDef = def.not(); // No deforestation appears as 1
  44
  45 ////////////////////////////////////////////////////////////////// Forest loss at any time / no loss (GFW) //////
  46 var endYearN = endYear-2000;// converts the end year to a number of two digits
  47 var startYearN = startYear-2000; // converts the end start to a number of two digits
  48 var loss = gfw.select("lossyear").lte(endYearN).and(gfw.select("lossyear").gte(startYearN)).unmask();
  49 var noLoss = loss.not();
  50
  51 ////////////////////////////////////////////////////////////////// Tree cover greater than 75% in 2000 (GFW) //////
  52 var tc75_2000 = gfw.select("treecover2000").gt(tcMaxThres);
  53
  54 ////////////////////////////////////////////////////////////////// Tree Cover criteria (USGS): //////
  55 // The USGS dataset has TC data for 2005, 2010, and 2015, so it sets a conditional
  56 // to select the TC dataset closest to the endYear
  57 var tcYear;
  58 if (endYear < 2007) {tcYear = 2005;} // this conditional helps to select the TC dataset closest to the endYear
  59 else if (endYear >= 2008 && endYear <= 2012) {tcYear = 2010;}
  60 else if (endYear > 2013) {tcYear = 2015;}
  61 // Function for applying a filter to reduce noise in the TC USGS outputs (years 2005 and 2010 are specially noisy)
  62 var filter = function (image) {
  63   // Applies a 90m X 90m filter (default options)
  64   var imageFiltered = image.focal_mode();
  65   // This is only for visualization purposes. The reproject is sufficient to force the computation to occur at native scale.
  66   return imageFiltered.reproject('EPSG:4326', null, 30);
  67 };
  68
  69 // Tree cover greater than 75% in 2015 or around the end of the study period (USGS)
  70 var tc75_endYear = usgs.filterBounds(aoi).select("tree_canopy_cover")
  71   .filterMetadata("year","equals",tcYear).mean().gt(tcMaxThres); // mean is only to convert it into a single image rather than image collection with only one
  72 var tc75_endYear_fil = filter (tc75_endYear);
  73
  74 // Tree cover greater or equal than 30% and lower or equal than 75% in 2015 or around the end of the study period (USGS)
  75 var tc30_endYear = usgs.filterBounds(aoi).select("tree_canopy_cover")
  76   .filterMetadata("year","equals",tcYear).mean().gt(tcMinThres); // mean is only to convert it into a single image rather than image collection with only one
  77 var tcLess75_endYear = usgs.filterBounds(aoi).select("tree_canopy_cover")
  78   .filterMetadata("year","equals",tcYear).mean().lte(tcMaxThres);
  79 var tc30_75_endYear = tc30_endYear.and(tcLess75_endYear);
  80 var tc30_75_endYear_fil = filter (tc30_75_endYear);
  81
  82 ////////////////////////////////////////////////////////////////// Forest cover during all the study period (MapBiomass) //////
  83 var rename = function (image){// Funcion for assigning the same name to all bands
  84   return image.select(0).rename("b1");
  85   var mapBiomass_r= mapBiomass.map(rename);
  86   var mapBiomass_fil = mapBiomass_r.filter(ee.Filter.and//Creates an collection containing the years within the study period (untill 2018)
  87     ee.Filter.gte('year', startYear),
  88     ee.Filter.lte('year', endYear));
  89 var mapBiomass_minMax = mapBiomass_fil.reduce(ee.Reducer.minMax()).rename("min","max");
  90 var mapBiomass_range = mapBiomass_minMax.expression('b\'\min\'-b\'\max\'').rename("range");
  91 var forestAll = mapBiomass_minMax.select("max").lte(6)//https://storage.googleapis.com/mapbiomas-public/RAISG/COLECAO2/LEGENDA/codigo_de_la_leyenda_coleccion-2.pdf
  92   .and(mapBiomass_range.eq(0)).rename("allForest");//forest is 3 or 6 in the entire Acre-Ucayali region during all years
  93
  94 ////////////////////////////////////////////////////////////////// Forest / non-forest at the end of the study period (MapBiomass) //////
  95 var forestEndYear = mapBiomass_r.filter(ee.Filter.eq("year",endYear)).mean().lte(6); //mean is only to convert it into a single image rather than image collection with only one im
  96 var noForestEndYear = forestEndYear.not();

  98 ////////////////////////////////////////////////////////////////// Selection of intact, disturbed, and deforested based on the above criteria ///////////////
  99
 100 ////////////////////////////////////////////////////////////////// Intact forest (1)
 101 //Criteria: never classified as deforested, TC>75% in 2000,
 102 //no forest loss, TC>75% in 2015 (or around the end of the study period), classified as forest during all the study period)
 103 var intactForest = noDef.and(tc75_2000).and(noLoss)
 104   .and(tc75_endYear).and(forestAll).clip(aoi);
 105
 106 ////////////////////////////////////////////////////////////////// Degraded forest (2)
 107 //Criteria: Deforested at some point, TC>=30<=75% in 2015 (or around the end of the study period),
 108 //and classified as forest at the end of the study period)
 109 var degradedForest = def.and(tc30_75_endYear_fil)
 110   .and(forestEndYear).remap([0,1],[0,2]).clip(aoi);
 111
 112 ////////////////////////////////////////////////////////////////// Deforested (3)
 113 //Criteria: classified as deforested at some point, forest loss at some point,
 114 // and classified as non-forest at the end of the study period)
 115 var deforested = def.and(loss)
 116   .and(noForestEndYear).remap([0,1],[0,3]).clip(aoi);
 117
 118 ////////////////////////////////////////////////////////////////// Merges classes and adds the result to the map (Using Image.cat to combine provokes an error in the sampling)
 119 var IntactDefDef = intactForest.add(degradedForest).add(deforested).remap([1,2,3],[1,2,3]).rename("class");
 120 Map.addLayer(IntactDefDef, {"opacity":1,"bands":["class"],"palette":["#0ff93b","ff6131","b05aff"]}, "Intact, Disturbed, and Deforested");
 121 Map.centerObject(aoi,10);
 122

```

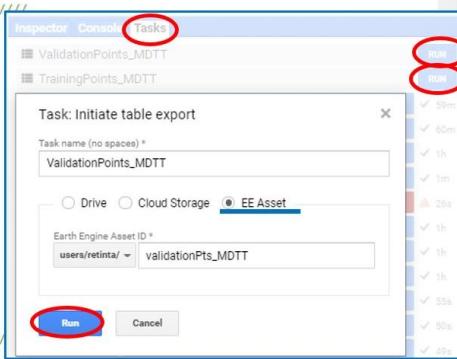
```

124 ////////////////////////////////////////////////////////////////// Random Sampling //////////////////////////////////////////////////////////////////
125
126 // Creates a random sample based on the user-defined number of sampling points per class
127 var samplingPts = IntactDegDef.stratifiedSample({
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.gte('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.table.toAsset({collection:training,
165   description:"TrainingPoints_" + outputName,
166   assetId: "trainingPts_" + outputName
167 });
168
169 Export.table.toAsset({collection: validation,
170   description:"ValidationPoints_" + outputName,
171   assetId: "validationPts_" + outputName
172 });
173
174 //////////////////////////////////////////////////////////////////
175 print("All done");

```

Annotations for the code:

- Line 127: Randomly selects the user-defined number of samples per class
- Line 138: Divides the sampling points into training (90%) and validation (10%) datasets
- Line 144: Removes any points closer than 500 meters of each other to ensure training samples are uncorrelated with validation samples
- Line 156: Prints the resulting number of training and validation points in the console and displays them in the map
- Line 164: Exports the results as GEE assets (used as inputs of the map classified into intact, degraded, and deforested)



Output

This code outputs two datasets: training points and validation points.

GEE assets

Table: trainingPts_MDTT				Table: validationPts_MDTT			
	DESCRIPTION	FEATURES	PROPERTIES		DESCRIPTION	FEATURES	PROPERTIES
Feature Index	class (Long)	random (Float)	system:index (String)	Feature Index	class (Long)	random (Float)	system:index (String)
0	1	0.53973746698 40993		0	1	0.92873632291 16009	
1	1	0.17310481412 728573		1	1	0.99629825895 20231	
2	1	0.30112765200 55456		2	1	0.96686432932 10513	
3	1	0.52621660336 93878		3	1	0.93932844944 80373	
4	1	0.08721550293 471692		4	1	0.95291402489 2686	

Map displayed in GEE

The figure shows a QGIS interface with the following components:

- Top Bar:** Includes "Get Link", "Save", "Run", "Reset", "Apps", and a gear icon.
- Inspector Panel:** Shows "Training points 1021" and "Validation points 152".
- Code Editor:** Displays R code for MTDD Sampling, including imports for GFW, USGS_TC, MAPBiOM_TOMAS, RAISG, and studyArea, and a detailed algorithm description.
- Layers Panel:** Shows checkboxes for "Validation Points", "Training Points", and "Intact, Disturbed, and Deforested".
- Visualization Parameters Panel:** Allows selecting "1 band (Grayscale)" or "3 bands (RGB)" and "class". It includes a "Range" slider from 1 to 3, "Opacity" at 1.00, and "Gamma" and "Palette" options. A "Import" button is also present.
- Map View:** Displays a map of the Amazon region with a green background. Overlaid are black dots representing training and validation points, and a network of blue lines representing rivers. A legend on the right identifies "Intact forest", "Deforestation", and "Degradation".

3.3.2. Degradation and deforestation map

This section demonstrates how to run this [code](#) to produce a map classified into intact forest, degradation, and deforestation.

Inputs

The user has to enter the following inputs:

```
MTDD_DisturbancesMap
 1 // Imports (4 entries) 
 2 > var MAPBIOMAS: ImageCollection users/retinta/MachineLearning/MapBiomassLcCol
 3 > var tp: Table users/retinta/Tutorials/trainingPts_MDTT
 4 > var vp: Table users/retinta/Tutorials/validationPts_MDTT
 5 > var studyArea: Table users/retinta/Tutorials/CaseStudy1
 6
 7 //////////////////////////////////////////////////////////////////// MTDD ALGORITHM ///////////////////////////////////
 8 //////////////////////////////////////////////////////////////////// Clasification /////////////////////////////////
 9 //////////////////////////////////////////////////////////////////// Outputs an image classified as Non Forest (0), Intact Forest (1), Disturbed Forest (2), //////
10 //////////////////////////////////////////////////////////////////// and Deforestation (3), also VALIDATES the model and exports the results in csv format //////
11 //////////////////////////////////////////////////////////////////// Based on Wang et al. (2019) and adapted by Reygadas et al. 2021 to the Southwestern //////
12 //////////////////////////////////////////////////////////////////// Amazon to detect intact, disturbed, and deforested areas//////
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 startDayB = '01-01';
26 var endDayB = '12-31';
27 var aoiB = studyArea;
28 var maskTheseB = ['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 mapBiomass= MAPBIOMAS; // Annual Land Cover
36
37 // Defines an output name that will be added to these identifiers: MTDD_Classified
38 var outName = "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

Running the code

Execute the code by clicking run. Once it is all done, go to the task console and click run to export the results as a raster (map classified) and csv files (overall accuracy and error matrix).

```
40 ////////////////////////////////////////////////////////////////// Function for calculating ALL METRICS //////////////////////////////////////////////////////////////////
41
42 - var metricsGral = function (startYear, endYear, startDay, endDay, aoi, maskThese){ ← Start of the function that calculates all 66 metrics
43
44 ////////////////////////////////////////////////////////////////// Time Series Trajectories //////////////////////////////////////////////////////////////////
45 // Builds an annual cloud, cloud shadow, snow, and water masked medoid composite of Landsat
46 // Surface Reflectance TM-equivalent bands 1(blue),2(Green),3(Red),4(NIR),5(SWIR1640),7(SWIR2130)
47 var ltgee = require('users/emaprlab/public/Modules/LandTrendR.js');// Requires the LandTrendR Library
48 var annualSRC = ltgee.buildSRcollection(startYear, endYear, startDay, endDay, aoi, maskThese);
49
50 // Function for converting original Surface Reflectance (16-bit signed integer) values to 0-1 range
51 // This is not a crucial step but will keep a more homogeneous range of values between indices(NDVI,NDWI1,SAVI) and bands(B5 and B7)
52 - var multiply = function (image) {
53   var multiplication = image.multiply ee.Image(0.0001);
54   return multiplication.copyProperties(image, ['system:time_start']);
55 };
56 var annualSRC_md = annualSRC.map(multiply);
57
58 // Function for adding a time band that will be needed to calculate temporal metrics
59 - var createTimeBand = function(image) {
60   // Scales milliseconds by a large constant to avoid very small slopes
61   // in the linear regression output (temporal metrics)
62   var time = image.metadata('system:time_start').divide(1e18).rename('time');
63   return image.addBands(time);
64 };
65 var annualSRC_md_tm = annualSRC_md.map(createTimeBand);
66
67 // Function for adding indices as new bands to each image in the collection
68 - var addIndices = function(image) {
69   var ndvi = image.expression('(b('B4')-b('B3'))/(b('B4')+b('B3'))').rename('NDVI');
70   var ndwi2130 = image.expression('(b('B4')-b('B7'))/(b('B4')+b('B7'))').rename('NDWI2130');
71   var ndwi1640 = image.expression('(b('B4')-b('B5'))/(b('B4')+b('B5'))').rename('NDWI1640');
72   var savi = image.expression('1.5*((b('B4')-b('B3'))/(b('B4')+b('B3'))+0.5)').rename('SAVI');
73   return image.addBands([ndvi,ndwi2130,ndwi1640,savi]);
74 };
75 var annualSRC_md_tm_indices = annualSRC_md_tm.map(addIndices);
76
```

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','NDWI2130','NDWI1640','SAVI'])
78 .reduce(ee.Reducer.min());
79 var max = annualSRC_md_tm_indices.select(['B5','B7','NDVI','NDWI2130','NDWI1640','SAVI'])
80 .reduce(ee.Reducer.max());
81 var range = max.subtract(min).rename(['B5_range','B7_range','NDVI_range','NDWI2130_range','NDWI1640_range','SAVI_range']);
82 var mean = annualSRC_md_tm_indices.select(['B5','B7','NDVI','NDWI2130','NDWI1640','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','NDWI2130','NDWI1640','SAVI'])
87 .reduce(ee.Reducer.stdDev());
88 var cv = mean.divide(stdDev).rename(['B5_cv','B7_cv','NDVI_cv','NDWI2130_cv','NDWI1640_cv','SAVI_cv']);
89 var kurt = annualSRC_md_tm_indices.select(['B5','B7','NDVI','NDWI2130','NDWI1640','SAVI'])
90 .reduce(ee.Reducer.kurtosis());
91 var skew = annualSRC_md_tm_indices.select(['B5','B7','NDVI','NDWI2130','NDWI1640','SAVI'])
92 .reduce(ee.Reducer.skew());
93
94 ////////////////////////////////////////////////////////////////// Temporal metrics /////
95 // Slope (outputs 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_slp');
98 var slopeB7 = annualSRC_md_tm_indices.select(['time','B7'])
99 .reduce(ee.Reducer.linearFit()).select('scale').rename('B7_slp');
100 var slopeNDVI = annualSRC_md_tm_indices.select(['time','NDVI'])
101 .reduce(ee.Reducer.linearFit()).select('scale').rename('NDVI_slp');
102 var slopeNDWI2130 = annualSRC_md_tm_indices.select(['time','NDWI2130'])
103 .reduce(ee.Reducer.linearFit()).select('scale').rename('NDWI2130_slp');
104 var slopeNDWI1640 = annualSRC_md_tm_indices.select(['time','NDWI1640'])
105 .reduce(ee.Reducer.linearFit()).select('scale').rename('NDWI1640_slp');
106 var slopeSAVI = annualSRC_md_tm_indices.select(['time','SAVI'])
107 .reduce(ee.Reducer.linearFit()).select('scale').rename('SAVI_slp');
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 });
114 var diffFilter = ee.Filter.maxDifference({ // Establishes the 5-year filter
115   difference: 78892380000, // 2.5 years in milliseconds, the filter selects 2 years before and after the target year
116   leftField: 'system:time_start', // therefore, the extreme windows are made of only 3-4 years
117   rightField: 'system:time_start'
118 });
119 var fiveWindowJoin = join.apply({// Collection in which each image is associated with the 5-year window images (see properties:
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 mvSlp = 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 = mvSlp.reduceColumns(ee.Reducer.minMax(), ["system:time_start"]); //Gets the date range of images in the collection
134   var filter1 = mvSlp.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(), ["system:time_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 mxSlpB5 = maxAbsMovSlope('B5', 'B5_mxSlp');
146 var mxSlpB7 = maxAbsMovSlope('B7', 'B7_mxSlp');
147 var mxSlpNDVI = maxAbsMovSlope('NDVI', 'NDVI_mxSlp');
148 var mxSlpNDWI2130 = maxAbsMovSlope('NDWI2130', 'NDWI2130_mxSlp');
149 var mxSlpNDWI1640 = maxAbsMovSlope('NDWI1640', 'NDWI1640_mxSlp');
150 var mxSlpSAVI = maxAbsMovSlope('SAVI', 'SAVI_mxSlp');
151
152 //Value at last year
153 var rangeDates = annualSRC_md_tm_indices.reduceColumns(ee.Reducer.minMax(), ["system:time_start"]);
154 var lastYearFil = annualSRC_md_tm_indices.filter(ee.Filter.date(rangeDates.get('max')));
155 var lastYear = lastYearFil.select(['B5','B7','NDVI','NDWI2130','NDWI1640','SAVI']).toBands();
156 var lastYearVal = lastYear.rename(['B5_last','B7_last','NDVI_last','NDWI2130_last','NDWI1640_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,slopeNDWI2130,slopeNDWI1640,slopeSAVI,
162 mxSlpB5,mxSlpB7,mxSlpNDVI,mxSlpNDWI2130,mxSlpNDWI1640,mxSlpSAVI,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){// Funcion for assigning the same name to all bands
177   return image.select(0).rename("b1");
178 }
179 var mapBiomass_r= mapBiomass.map(rename);
180 ee.Filter.gte('year', startYearT,
181 ee.Filter.lte('year', endYearT));
182 // Function for detecting pixels covered by forest
183 //storage.googleapis.com/mapbiomas-public/RAISG/COLECAO2/LEGENDA/codigo_de_la_leyenda_coleccion-2.pdf
184 //forest is 3 or 6 in the entire Acre-Ucayali region during all years
185 var forest = function (image) {
186   return image.eq(3).or(image.eq(6)).rename("forest").copyProperties(image, ['year']);
187 }
188 var forestCol = mapBiomass.map(forest);
189 // Function for adding a time band that will be needed to calculate land covers per year
190 var createTimeBandMask = function(image) {
191   var time = image.metadata('year').rename('time');
192   return image.addBands(time);
193 };
194 var forestCol_tm = forestCol.map(createTimeBandMask);
195
196 // Forest in three consecutive years
197 // Creates a moving 3-year window
198 var join1 = ee.Join.saveAll({matchesKey: 'images'});
199 var difffilter1 = ee.Filter.maxDifference({difference: 1.5, leftField: 'year', rightField: 'year'});
200 var threeWindowJoin = join1.apply({primary: forestCol_tm, secondary: forestCol_tm, condition: difffilter1});
201
202 // Function for detecting forest cover over 3-year moving windows
203 var forest3years = function (invar, outvar){
204   // Calculates sum over 3-year windows
205   var f3y = ee.ImageCollection(threeWindowJoin.map(function(image) {
206     var forestCol_tm = ee.ImageCollection.fromImages(image.get('images'));
207     return ee.Image(image).addBands(forestCol_tm .select(["time",invar])
208       .reduce(ee.Reducer.sum()));
209   }));
210   // Extracts the maximum sum
211   return f3y.reduce(ee.Reducer.max());
212 };
213
214 // Applies the "detecting forest cover over 3-year" function to forest presence per year
215 var MaxForest3years = forest3years('forest', 'forest_3years').select("forest_sum_max");
216 // Gets the forest mask (areas that were forest at least three consecutive years)
217 var forestMask= MaxForest3years.gte(3);
218

```

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

```

218 ////////////////////////////////////////////////////////////////// Classificador 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 // Sobrepone los puntos de entrenamiento con las métricas*
229 var collectMetrics = function (feature){// usar una funcion 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: 50})
240 .train({features: trainingPoints, classProperty:'class',
241   inputProperties:[ '0_B5_min','0_B7_min','0_NDWI_min','0_NDWI2130_min','0_NDWI1640_min','0_SAVI_min',
242   '1_B5_max','1_B7_max','1_NDWI_max','1_NDWI2130_max','1_NDWI1640_max','1_SAVI_max',
243   '2_B5_range','2_B7_range','2_NDWI_range','2_NDWI2130_range','2_NDWI1640_range','2_SAVI_range',
244   '3_B5_mean','3_B7_mean','3_NDWI_mean','3_NDWI2130_mean','3_NDWI1640_mean','3_SAVI_mean',
245   '4_B5_stdDev','4_B7_stdDev','4_NDWI_stdDev','4_NDWI2130_stdDev','4_NDWI1640_stdDev','4_SAVI_stdDev',
246   '5_B5_cv','5_B7_cv','5_NDWI2130_cv','5_NDWI1640_cv','5_SAVI_cv',
247   '6_B5_kurtosis','6_B7_kurtosis','6_NDWI_kurtosis','6_NDWI2130_kurtosis','6_NDWI1640_kurtosis','6_SAVI_kurtosis',
248   '7_B5_skew','7_B7_skew','7_NDWI_skew','7_NDWI2130_skew','7_NDWI1640_skew','7_SAVI_skew',
249   '8_B5_slp','9_B7_slp','10_NDWI_slp','11_NDWI2130_slp','12_NDWI1640_slp','13_SAVI_slp',
250   '14_B5_mxSlp','15_B7_mxSlp','16_NDWI_mxSlp','17_NDWI2130_mxSlp','18_NDWI1640_mxSlp','19_SAVI_mxSlp',
251   '20_B5_last','20_B7_last','20_NDWI1640_last','20_NDWI2130_last','20_SAVI_last']
252 });
253
254
255 // Clasifica las métricas deseadas**
256 var metricsMask = metricsClassification.mask(forestMask); // Enmascara las areas no forestales
257 var classified = metricsMask.classify(classifier); //No bosque (0), bosque intacto (1), bosque degradado (2), áreas deforestadas (3)
258 print("Mapa clasificado");
259

```

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

```

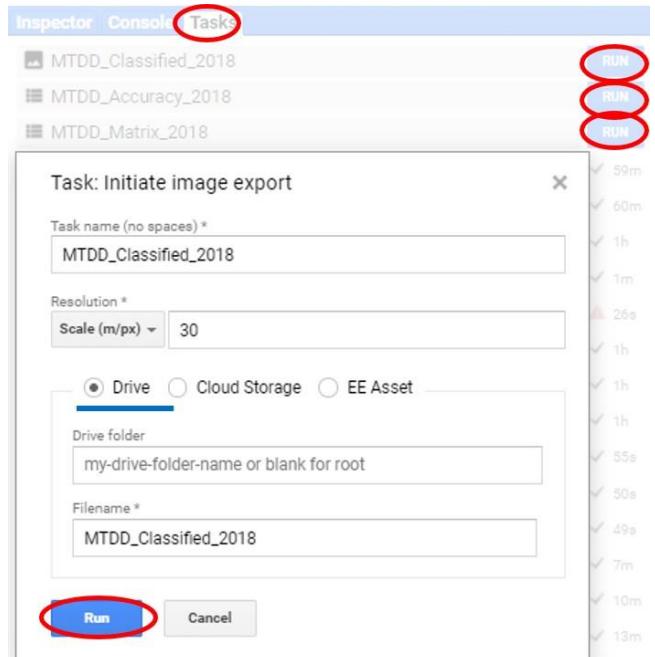
269 ///////////////////////////////////////////////////////////////////Post-classification filtering to reduce noise/////////////////////////////////////////////////////////////////
270
271 // Applies a 90m X 90m filter (default options)
272 var classified_fil = classified.focal_mode().mask(forestMask);
273 // This is only for visualization purposes. The reproject is sufficient
274 // to force the computation to occur at native scale.
275 var classified_fil_vis = classified_fil.reproject('EPSG:4326', null, 30);
276 // Displays the results
277 //Map.setCenterObject(aoi,10);
278 //Map.addLayer(classified_fil_vis.clip(aoiC),
279 //    {"opacity":1,"bands":["classification"],"min":0,"max":3,"palette":[ "#ffffff", "#7dff5c", "#0a9b15", "#ff5544"]},
280 //    "Classification");
281
282 ////////////////////////////////////////////////////////////////// Validation //////////////////////////////////////////////////////////////////
283
284 // Overlays the validation points over the metrics
285 var validationCol = validationPts.map(collectMetrics);
286 var validationPoints = validationCol.flatten();
287 //print("Metrics collected in validation points",validationPoints);
288
289 // Classify the validation data
290 var validated = validationPoints.classify(classifier);
291
292 // Gets a confusion matrix representing expected accuracy
293 var valAccuracy = validated.errorMatrix("class","classification");
294 //print('Validation error matrix: ', valAccuracy);
295 //print('Validation overall accuracy: ', valAccuracy.accuracy());
296
297 ////////////////////////////////////////////////////////////////// Results exportation //////////////////////////////////////////////////////////////////
298
299 // Exports the image classified into Intact, Degraded forest, and deforested
300 Export.image.toDrive({image:classified_fil,
301   description: "MTDD_Classified_" + outName ,
302   fileNamePrefix: "MTDD_Classified_" + outName,
303   region:aoiI,
304   scale:30,
305   maxPixels:60000000
306 });
307
308 // Exports the confusion matrix
309 var toExportMatrix = ee.Feature(null, {matrix: valAccuracy.array()});
310 Export.table.toDrive({
311   collection: ee.FeatureCollection(toExportMatrix),
312   description: "MTDD_Matrix_" + outName,
313   fileFormat: 'CSV'
314 });
315
316 // Exports the validation overall accuracy
317 var toExportAccuracy = ee.Feature(null, {matrix: valAccuracy.accuracy()});
318 Export.table.toDrive({
319   collection: ee.FeatureCollection(toExportAccuracy),
320   description: "MTDD_Accuracy_" + outName,
321   fileFormat: 'CSV'
322 });
323
324
325
326 print("All done");

```

Applies a filter to reduce noise

Validates the results by using the validation dataset and generating a confusion matrix

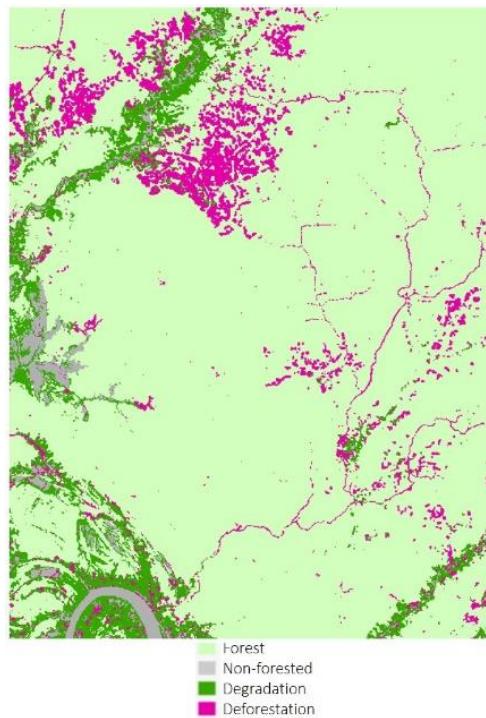
Exports the classified image as a raster, and the confusion matrix and overall accuracy as a csv file



Output

This code outputs a map classified into non-forest, intact forest, degradation, and deforestation.

Raster (“.tif” file)



Overall accuracy and confusion matrix (“.csv” files)

	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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