

# Package ‘sits’

May 9, 2024

**Type** Package

**Version** 1.5.0

**Title** Satellite Image Time Series Analysis for Earth Observation Data Cubes

**Maintainer** Gilberto Camara <gilberto.camara.inpe@gmail.com>

**Description** An end-to-end toolkit for land use and land cover classification using big Earth observation data, based on machine learning methods applied to satellite image data cubes, as described in Simoes et al (2021) <[doi:10.3390/rs13132428](https://doi.org/10.3390/rs13132428)>. Builds regular data cubes from collections in AWS, Microsoft Planetary Computer, Brazil Data Cube, and Digital Earth Africa using the Spatio-temporal Asset Catalog (STAC) protocol (<<https://stacspec.org/>> and the 'gdalcubes' R package developed by Appel and Pebesma (2019) <[doi:10.3390/data4030092](https://doi.org/10.3390/data4030092)>. Supports visualization methods for images and time series and smoothing filters for dealing with noisy time series. Includes functions for quality assessment of training samples using self-organized maps as presented by Santos et al (2021) <[doi:10.1016/j.isprsjprs.2021.04.014](https://doi.org/10.1016/j.isprsjprs.2021.04.014)>. Provides machine learning methods including support vector machines, random forests, extreme gradient boosting, multi-layer perceptrons, temporal convolutional neural networks proposed by Pelletier et al (2019) <[doi:10.3390/rs11050523](https://doi.org/10.3390/rs11050523)>, residual networks by Fawaz et al (2019) <[doi:10.1007/s10618-019-00619-1](https://doi.org/10.1007/s10618-019-00619-1)>, and temporal attention encoders by Garnot and Landrieu (2020) <[doi:10.48550/arXiv.2007.00586](https://doi.org/10.48550/arXiv.2007.00586)>. Performs efficient classification of big Earth observation data cubes and includes functions for post-classification smoothing based on Bayesian inference, and methods for uncertainty assessment. Enables best practices for estimating area and assessing accuracy of land change as recommended by Olofsson et al (2014) <[doi:10.1016/j.rse.2014.02.015](https://doi.org/10.1016/j.rse.2014.02.015)>. Minimum recommended requirements: 16 GB RAM and 4 CPU dual-core.

**Encoding** UTF-8

**Language** en-US

**Depends** R (>= 4.0.0)

**URL** <https://github.com/e-sensing/sits/>,  
<https://e-sensing.github.io/sitsbook/>

**BugReports** <https://github.com/e-sensing/sits/issues>

**License** GPL-2

**ByteCompile** true

**LazyData** true

**Imports** yaml, dplyr (>= 1.0.0), gdalUtilities, grDevices, graphics, lubridate, parallel (>= 4.0.5), purrr (>= 1.0.2), Rcpp, rstac (>= 1.0.0), sf (>= 1.0-12), showtext, sysfonts, slider (>= 0.2.0), stats, terra (>= 1.7-71), tibble (>= 3.1), tidyr (>= 1.2.0), torch (>= 0.11.0), utils

**Suggests** aws.s3, caret, cli, covr, dendextend, dtwclust, DiagrammeR, digest, e1071, exactextractr, FNN, future, gdalcubes (>= 0.6.0), geojsonsf, ggplot2, httr, jsonlite, kohonen (>= 3.0.11), leafem (>= 0.2.0), leaflet (>= 2.2.0), luz (>= 0.4.0), methods, mgcv, nnet, openxlsx, randomForest, randomForestExplainer, RColorBrewer, RcppArmadillo (>= 0.12), scales, spdep, stars (>= 0.6), stringr, supercells (>= 1.0.0), testthat (>= 3.1.3), tmap (>= 3.3), torchopt (>= 0.1.2), tools, xgboost

**Config/testthat/edition** 3

**Config/testthat/parallel** false

**Config/testthat/start-first** cube, raster, regularize, data, ml

**LinkingTo** Rcpp, RcppArmadillo

**RoxygenNote** 7.3.1

**Collate** 'api\_accessors.R' 'api\_accuracy.R' 'api\_apply.R' 'api\_band.R' 'api\_bbox.R' 'api\_block.R' 'api\_check.R' 'api\_chunks.R' 'api\_classify.R' 'api\_clean.R' 'api\_cluster.R' 'api\_colors.R' 'api\_combine\_predictions.R' 'api\_comp.R' 'api\_conf.R' 'api\_csv.R' 'api\_cube.R' 'api\_data.R' 'api\_debug.R' 'api\_download.R' 'api\_environment.R' 'api\_factory.R' 'api\_file\_info.R' 'api\_file.R' 'api\_gdal.R' 'api\_gdalcubes.R' 'api\_jobs.R' 'api\_kohonen.R' 'api\_label\_class.R' 'api\_merge.R' 'api\_mixture\_model.R' 'api\_ml\_model.R' 'api\_mosaic.R' 'api\_opensearch.R' 'api\_parallel.R' 'api\_period.R' 'api\_plot\_time\_series.R' 'api\_plot\_raster.R' 'api\_plot\_vector.R' 'api\_point.R' 'api\_predictors.R' 'api\_raster.R' 'api\_raster\_sub\_image.R' 'api\_raster\_terra.R' 'api\_reclassify.R' 'api\_reduce.R' 'api\_regularize.R' 'api\_roi.R' 'api\_s2tile.R' 'api\_samples.R' 'api\_segments.R' 'api\_select.R' 'api\_sf.R' 'api\_shp.R' 'api\_signal.R' 'api\_smooth.R' 'api\_smote.R' 'api\_som.R' 'api\_source.R' 'api\_source\_aws.R' 'api\_source\_bdc.R' 'api\_source\_cdse.R' 'api\_source\_deafrica.R' 'api\_source\_hls.R' 'api\_source\_local.R'

'api\_source\_mpc.R' 'api\_source\_sdc.R' 'api\_source\_stac.R'  
 'api\_source\_usgs.R' 'api\_space\_time\_operations.R' 'api\_stac.R'  
 'api\_stats.R' 'api\_summary.R' 'api\_tibble.R' 'api\_tile.R'  
 'api\_timeline.R' 'api\_torch.R' 'api\_torch\_psetae.R' 'api\_ts.R'  
 'api\_tuning.R' 'api\_uncertainty.R' 'api\_utils.R' 'api\_values.R'  
 'api\_variance.R' 'api\_vector.R' 'api\_vector\_info.R'  
 'api\_view.R' 'RcppExports.R' 'data.R' 'sits-package.R'  
 'sits\_apply.R' 'sits\_accuracy.R' 'sits\_active\_learning.R'  
 'sits\_bands.R' 'sits\_bbox.R' 'sits\_classify.R' 'sits\_colors.R'  
 'sits\_combine\_predictions.R' 'sits\_config.R' 'sits\_csv.R'  
 'sits\_cube.R' 'sits\_cube\_copy.R' 'sits\_clean.R'  
 'sits\_cluster.R' 'sits\_factory.R' 'sits\_filters.R'  
 'sits\_geo\_dist.R' 'sits\_get\_data.R' 'sits\_imputation.R'  
 'sits\_labels.R' 'sits\_label\_classification.R' 'sits\_lighttae.R'  
 'sits\_machine\_learning.R' 'sits\_merge.R' 'sits\_mixture\_model.R'  
 'sits\_mlp.R' 'sits\_mosaic.R' 'sits\_model\_export.R'  
 'sits\_patterns.R' 'sits\_plot.R' 'sits\_predictors.R'  
 'sits\_reclassify.R' 'sits\_reduce.R' 'sits\_regularize.R'  
 'sits\_resnet.R' 'sits\_sample\_functions.R' 'sits\_segmentation.R'  
 'sits\_select.R' 'sits\_sf.R' 'sits\_smooth.R' 'sits\_som.R'  
 'sits\_summary.R' 'sits\_tae.R' 'sits\_tempcnn.R'  
 'sits\_timeline.R' 'sits\_train.R' 'sits\_tuning.R' 'sits\_utils.R'  
 'sits\_uncertainty.R' 'sits\_validate.R' 'sits\_view.R'  
 'sits\_variance.R' 'sits\_xlsx.R' 'zzz.R'

**NeedsCompilation** yes

**Author** Rolf Simoes [aut],  
 Gilberto Camara [aut, cre],  
 Felipe Souza [aut],  
 Lorena Santos [aut],  
 Pedro Andrade [aut],  
 Karine Ferreira [aut],  
 Alber Sanchez [aut],  
 Gilberto Queiroz [aut]

**Repository** CRAN

**Date/Publication** 2024-05-09 19:00:03 UTC

## R topics documented:

sits-package . . . . .	6
cerrado_2classes . . . . .	7
impute_linear . . . . .	7
plot . . . . .	8
plot.class_cube . . . . .	9
plot.class_vector_cube . . . . .	10
plot.geo_distances . . . . .	12
plot.patterns . . . . .	13
plot.predicted . . . . .	14

plot.probs_cube . . . . .	15
plot.probs_vector_cube . . . . .	16
plot.raster_cube . . . . .	18
plot.rfor_model . . . . .	19
plot.sits_accuracy . . . . .	20
plot.sits_cluster . . . . .	21
plot.som_evaluate_cluster . . . . .	22
plot.som_map . . . . .	23
plot.torch_model . . . . .	24
plot.uncertainty_cube . . . . .	25
plot.uncertainty_vector_cube . . . . .	26
plot.variance_cube . . . . .	28
plot.vector_cube . . . . .	29
plot.xgb_model . . . . .	31
point_mt_6bands . . . . .	32
samples_l8_rondonia_2bands . . . . .	32
samples_modis_ndvi . . . . .	33
sits_accuracy . . . . .	33
sits_apply . . . . .	35
sits_as_sf . . . . .	38
sits_bands . . . . .	39
sits_bbox . . . . .	41
sits_classify . . . . .	42
sits_clean . . . . .	46
sits_cluster_clean . . . . .	48
sits_cluster_dendro . . . . .	49
sits_cluster_frequency . . . . .	51
sits_colors . . . . .	52
sits_colors_qgis . . . . .	53
sits_colors_reset . . . . .	54
sits_colors_set . . . . .	54
sits_colors_show . . . . .	55
sits_combine_predictions . . . . .	56
sits_confidence_sampling . . . . .	58
sits_config . . . . .	60
sits_config_show . . . . .	61
sits_cube . . . . .	61
sits_cube_copy . . . . .	67
sits_factory_function . . . . .	69
sits_filter . . . . .	70
sits_formula_linear . . . . .	71
sits_formula_logref . . . . .	72
sits_geo_dist . . . . .	73
sits_get_data . . . . .	74
sits_impute . . . . .	78
sits_kfold_validate . . . . .	79
sits_labels . . . . .	80
sits_labels_summary . . . . .	82

sits_label_classification . . . . .	83
sits_lighttae . . . . .	85
sits_list_collections . . . . .	87
sits_merge . . . . .	88
sits_mgrs_to_roi . . . . .	89
sits_mixture_model . . . . .	90
sits_mlp . . . . .	92
sits_model_export . . . . .	95
sits_mosaic . . . . .	95
sits_patterns . . . . .	97
sits_predictors . . . . .	98
sits_pred_features . . . . .	99
sits_pred_normalize . . . . .	100
sits_pred_reference . . . . .	101
sits_pred_sample . . . . .	101
sits_reclassify . . . . .	102
sits_reduce . . . . .	105
sits_reduce_imbalance . . . . .	107
sits_regularize . . . . .	109
sits_resnet . . . . .	111
sits_rfor . . . . .	114
sits_run_examples . . . . .	115
sits_run_tests . . . . .	116
sits_sample . . . . .	116
sits_sampling_design . . . . .	117
sits_segment . . . . .	118
sits_select . . . . .	120
sits_sgolay . . . . .	122
sits_slic . . . . .	123
sits_smooth . . . . .	125
sits_som . . . . .	127
sits_som_clean_samples . . . . .	129
sits_som_evaluate_cluster . . . . .	130
sits_stats . . . . .	131
sits_stratified_sampling . . . . .	132
sits_svm . . . . .	133
sits_tae . . . . .	135
sits_tempcnn . . . . .	137
sits_timeline . . . . .	140
sits_to_csv . . . . .	141
sits_to_xlsx . . . . .	142
sits_train . . . . .	143
sits_tuning . . . . .	144
sits_tuning_hparams . . . . .	146
sits_uncertainty . . . . .	147
sits_uncertainty_sampling . . . . .	149
sits_validate . . . . .	151
sits_variance . . . . .	152

sits_view . . . . .	154
sits_whittaker . . . . .	158
sits_xgboost . . . . .	159
summary.class_cube . . . . .	161
summary.raster_cube . . . . .	162
summary.sits . . . . .	163
summary.sits_accuracy . . . . .	164
summary.sits_area_accuracy . . . . .	165
'sits_labels<-'. . . . .	166

<b>Index</b>	<b>168</b>
--------------	------------

---

sits-package	<i>sits</i>
--------------	-------------

---

## Description

Satellite Image Time Series Analysis for Earth Observation Data Cubes

## Purpose

The SITS package provides a set of tools for analysis, visualization and classification of satellite image time series. It includes methods for filtering, clustering, classification, and post-processing.

## Author(s)

**Maintainer:** Gilberto Camara <gilberto.camara.inpe@gmail.com>

Authors:

- Rolf Simoes <rolf.simoes@inpe.br>
- Felipe Souza <felipe.carvalho@inpe.br>
- Lorena Santos <lorena.santos@inpe.br>
- Pedro Andrade <pedro.andrade@inpe.br>
- Karine Ferreira <karine.ferreira@inpe.br>
- Alber Sanchez <alber.ipia@inpe.br>
- Gilberto Queiroz <gilberto.queiroz@inpe.br>

## See Also

Useful links:

- <https://github.com/e-sensing/sits/>
- <https://e-sensing.github.io/sitsbook/>
- Report bugs at <https://github.com/e-sensing/sits/issues>

---

cerrado_2classes	<i>Samples of classes Cerrado and Pasture</i>
------------------	---

---

**Description**

A dataset containing a tibble with time series samples for the Cerrado and Pasture areas of the Mato Grosso state. The time series come from MOD13Q1 collection 5 images.

**Usage**

```
data(cerrado_2classes)
```

**Format**

A tibble with 736 rows and 7 variables: longitude: East-west coordinate of the time series sample (WGS 84), latitude (North-south coordinate of the time series sample in WGS 84), start\_date (initial date of the time series), end\_date (final date of the time series), label (the class label associated to the sample), cube (the name of the cube associated with the data), time\_series (list containing a tibble with the values of the time series).

---

impute_linear	<i>Replace NA values with linear interpolation</i>
---------------	--

---

**Description**

Remove NA by linear interpolation  
Remove NA by linear interpolation

**Usage**

```
impute_linear(data = NULL)  
impute_linear(data = NULL)
```

**Arguments**

data            A time series vector or matrix

**Value**

A set of filtered time series using the imputation function.  
A set of filtered time series using the imputation function.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

---

plot

*Plot time series*

---

### Description

This is a generic function. Parameters depend on the specific type of input. See each function description for the required parameters.

- sits tibble: see [plot.sits](#)
- patterns: see [plot.patterns](#)
- SOM map: see [plot.som\\_map](#)
- SOM evaluate cluster: see [plot.som\\_evaluate\\_cluster](#)
- classified time series: see [plot.predicted](#)
- raster cube: see [plot.raster\\_cube](#)
- vector cube: see [plot.vector\\_cube](#)
- random forest model: see [plot.rfor\\_model](#)
- xgboost model: see [plot.xgb\\_model](#)
- torch ML model: see [plot.torch\\_model](#)
- classification probabilities: see [plot.probs\\_cube](#)
- model uncertainty: see [plot.uncertainty\\_cube](#)
- classified cube: see [plot.class\\_cube](#)
- classified vector cube: see [plot.class\\_vector\\_cube](#)

### Usage

```
## S3 method for class 'sits'  
plot(x, y, ..., together = FALSE)
```

### Arguments

x	Object of class "sits".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
together	A logical value indicating whether the samples should be plotted together.

### Value

A series of plot objects produced by ggplot2 showing all time series associated to each combination of band and label, and including the median, and first and third quartile ranges.

### Author(s)

Gilberto Camara, <[gilberto.camara@inpe.br](mailto:gilberto.camara@inpe.br)>



**Examples**

```
if (sits_run_examples()) {  
  # plot sets of time series  
  plot(cerrado_2classes)  
}
```

---

plot.class\_cube      *Plot classified images*

---

**Description**

plots a classified raster using ggplot.

**Usage**

```
## S3 method for class 'class_cube'  
plot(  
  x,  
  y,  
  ...,  
  tile = x[["tile"]][[1]],  
  title = "Classified Image",  
  legend = NULL,  
  palette = "Spectral",  
  scale = 0.8  
)
```

**Arguments**

x	Object of class "class_cube".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
tile	Tile to be plotted.
title	Title of the plot.
legend	Named vector that associates labels to colors.
palette	Alternative RColorBrewer palette
scale	Scale to plot map (0.4 to 1.0)

**Value**

A color map, where each pixel has the color associated to a label, as defined by the legend parameter.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # label cube with the most likely class
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # plot the resulting classified image
  plot(label_cube)
}

```

---

plot.class\_vector\_cube

*Plot Segments*

---

**Description**

Plot vector classified cube

**Usage**

```

## S3 method for class 'class_vector_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  legend = NULL,
  seg_color = "black",
  line_width = 0.5,
  palette = "Spectral",
  scale = 0.8
)

```

**Arguments**

x	Object of class "segments".
...	Further specifications for <code>plot</code> .
tile	Tile to be plotted.
legend	Named vector that associates labels to colors.
seg_color	Segment color.
line_width	Segment line width.
palette	Alternative RColorBrewer palette
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot object with an RGB image or a B/W image on a color scale using the palette

**Note**

To see which color palettes are supported, please run

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # segment the image
  segments <- sits_segment(
    cube = cube,
    output_dir = tempdir()
  )
  # create a classification model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify the segments
  probs_segs <- sits_classify(
    data = segments,
    ml_model = rfor_model,
    output_dir = tempdir()
  )
  #
  # Create a classified vector cube
  class_segs <- sits_label_classification(
    cube = probs_segs,
    output_dir = tempdir(),
```

```
        multicores = 2,  
        memsize = 4  
    )  
    # plot the segments  
    plot(class_segs)  
}
```

---

plot.geo\_distances      *Make a kernel density plot of samples distances.*

---

## Description

Make a kernel density plot of samples distances.

## Usage

```
## S3 method for class 'geo_distances'  
plot(x, y, ...)
```

## Arguments

x	Object of class "geo_distances".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .

## Value

A plot showing the sample-to-sample distances and sample-to-prediction distances.

## Note

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

## Author(s)

Felipe Souza, <lipecaso@gmail.com>  
Rolf Simoes, <rolf.simoes@inpe.br>  
Alber Sanchez, <alber.ipia@inpe.br>

## References

Hanna Meyer and Edzer Pebesma, "Machine learning-based global maps of ecological variables and the challenge of assessing them" Nature Communications, 13,2022. DOI: 10.1038/s41467-022-29838-9.

## Examples

```
if (sits_run_examples()) {  
  # read a shapefile for the state of Mato Grosso, Brazil  
  mt_shp <- system.file("extdata/shapefiles/mato_grosso/mt.shp",  
    package = "sits"  
  )  
  # convert to an sf object  
  mt_sf <- sf::read_sf(mt_shp)  
  # calculate sample-to-sample and sample-to-prediction distances  
  distances <- sits_geo_dist(samples_modis_ndvi, mt_sf)  
  # plot sample-to-sample and sample-to-prediction distances  
  plot(distances)  
}
```

---

plot.patterns

*Plot patterns that describe classes*

---

## Description

Plots the patterns to be used for classification  
Given a sits tibble with a set of patterns, plot them.

## Usage

```
## S3 method for class 'patterns'  
plot(x, y, ..., bands = NULL, year_grid = FALSE)
```

## Arguments

x	Object of class "patterns".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
bands	Bands to be viewed (optional).
year_grid	Plot a grid of panels using labels as columns and years as rows. Default is FALSE.

## Value

A plot object produced by ggplot2 with one average pattern per label.

## Note

This code is reused from the dtwSat package by Victor Maus.

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>  
Victor Maus, <vwmaus1@gmail.com>

**Examples**

```
if (sits_run_examples()) {  
  # plot patterns  
  plot(sits_patterns(cerrado_2classes))  
}
```

---

plot.predicted      *Plot time series predictions*

---

**Description**

Given a sits tibble with a set of predictions, plot them

**Usage**

```
## S3 method for class 'predicted'  
plot(x, y, ..., bands = "NDVI", palette = "Harmonic")
```

**Arguments**

x	Object of class "predicted".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
bands	Bands for visualization.
palette	HCL palette used for visualization in case classes are not in the default sits palette.

**Value**

A plot object produced by ggplot2 showing the time series and its label.

**Note**

This code is reused from the dtwSat package by Victor Maus.

**Author(s)**

Victor Maus, <vwmaus1@gmail.com>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # Retrieve the samples for Mato Grosso
  # train an svm model
  ml_model <- sits_train(samples_modis_ndvi, ml_method = sits_svm)
  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  point_class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
  plot(point_class)
}

```

---

plot.probs_cube	<i>Plot probability cubes</i>
-----------------	-------------------------------

---

**Description**

plots a probability cube using stars

**Usage**

```

## S3 method for class 'probs_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  labels = NULL,
  palette = "YlGn",
  style = "cont",
  n_colors = 10,
  rev = FALSE,
  scale = 0.8
)

```

**Arguments**

x	Object of class "probs_cube".
...	Further specifications for <a href="#">plot</a> .
tile	Tile to be plotted.
labels	Labels to plot (optional).
palette	RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
n_colors	Number of colors to be shown
rev	Reverse order of colors in palette?
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot containing probabilities associated to each class for each pixel.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # plot the resulting probability cube
  plot(probs_cube)
}
```

---

plot.probs\_vector\_cube

*Plot probability vector cubes*

---

**Description**

plots a probability cube using stars

**Usage**

```
## S3 method for class 'probs_vector_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  labels = NULL,
  palette = "YlGn",
  style = "cont",
  rev = FALSE,
  scale = 0.8
)
```



**Arguments**

x	Object of class "probs_vector_cube".
...	Further specifications for <a href="#">plot</a> .
tile	Tile to be plotted.
labels	Labels to plot (optional).
palette	RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
rev	Reverse order of colors in palette?
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot containing probabilities associated to each class for each pixel.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # segment the image
  segments <- sits_segment(
    cube = cube,
    seg_fn = sits_slic(step = 5,
                      compactness = 1,
                      dist_fun = "euclidean",
                      avg_fun = "median",
                      iter = 20,
                      minarea = 10,
                      verbose = FALSE),
    output_dir = tempdir()
  )
  # classify a data cube
  probs_vector_cube <- sits_classify(
    data = segments,
    ml_model = rfor_model,
    output_dir = tempdir()
  )
}
```

```

    # plot the resulting probability cube
    plot(probs_vector_cube)
}

```

---

plot.raster\_cube      *Plot RGB data cubes*

---

## Description

Plot RGB raster cube

## Usage

```

## S3 method for class 'raster_cube'
plot(
  x,
  ...,
  band = NULL,
  red = NULL,
  green = NULL,
  blue = NULL,
  tile = x[["tile"]][[1]],
  date = NULL,
  palette = "RdYlGn",
  style = "cont",
  n_colors = 10,
  rev = FALSE,
  scale = 1
)

```

## Arguments

x	Object of class "raster_cube".
...	Further specifications for <a href="#">plot</a> .
band	Band for plotting grey images.
red	Band for red color.
green	Band for green color.
blue	Band for blue color.
tile	Tile to be plotted.
date	Date to be plotted.
palette	An RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
n_colors	Number of colors to be shown
rev	Reverse the color order in the palette?
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot object with an RGB image or a B/W image on a color scale using the pallete

**Note**

To see which colors are supported, please run `sits_colors()` Use `scale` parameter for general output control. If required, then set the other params individually

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # plot NDVI band of the second date date of the data cube
  plot(cube, band = "NDVI", date = sits_timeline(cube)[1])
}
```

---

plot.rfor\_model

*Plot Random Forest model*

---

**Description**

Plots the important variables in a random forest model.

**Usage**

```
## S3 method for class 'rfor_model'
plot(x, y, ...)
```

**Arguments**

<code>x</code>	Object of class "rf_model".
<code>y</code>	Ignored.
<code>...</code>	Further specifications for <code>plot</code> .

**Value**

A random forest object.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # Retrieve the samples for Mato Grosso  
  # train a random forest model  
  rf_model <- sits_train(samples_modis_ndvi, ml_method = sits_rfor())  
  # plot the model  
  plot(rf_model)  
}
```

---

plot.sits\_accuracy      *Plot confusion matrix*

---

**Description**

Plot a bar graph with informations about the confusion matrix

**Usage**

```
## S3 method for class 'sits_accuracy'  
plot(x, y, ..., title = "Confusion matrix")
```

**Arguments**

x	Object of class "plot.sits_accuracy".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
title	Title of plot.

**Value**

A plot object produced by the `ggplot2` package containing color bars showing the confusion between classes.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # show accuracy for a set of samples  
  train_data <- sits_sample(samples_modis_ndvi, frac = 0.5)  
  test_data <- sits_sample(samples_modis_ndvi, frac = 0.5)  
  # compute a random forest model  
  rfor_model <- sits_train(train_data, sits_rfor())  
  # classify training points  
  points_class <- sits_classify(  
    data = test_data, ml_model = rfor_model  
  )  
  # calculate accuracy  
  acc <- sits_accuracy(points_class)  
  # plot accuracy  
  plot(acc)  
}
```

---

plot.sits\_cluster      *Plot a dendrogram cluster*

---

**Description**

Plot a dendrogram

**Usage**

```
## S3 method for class 'sits_cluster'  
plot(x, ..., cluster, cutree_height, palette)
```

**Arguments**

x	sits tibble with cluster indexes.
...	Further specifications for <a href="#">plot</a> .
cluster	cluster object produced by 'sits_cluster' function.
cutree_height	dashed horizontal line to be drawn indicating the height of dendrogram cutting.
palette	HCL color palette.

**Value**

The dendrogram object.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

## Examples

```
if (sits_run_examples()) {  
  samples <- sits_cluster_dendro(cerrado_2classes,  
                                bands = c("NDVI", "EVI"))  
}
```

---

plot.som\_evaluate\_cluster

*Plot confusion between clusters*

---

## Description

Plot a bar graph with informations about each cluster. The percentage of mixture between the clusters.

## Usage

```
## S3 method for class 'som_evaluate_cluster'  
plot(x, y, ..., name_cluster = NULL, title = "Confusion by cluster")
```

## Arguments

x	Object of class "plot.som_evaluate_cluster".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
name_cluster	Choose the cluster to plot.
title	Title of plot.

## Value

A plot object produced by the `ggplot2` package containing color bars showing the confusion between classes.

## Note

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

## Author(s)

Lorena Santos <lorena.santos@inpe.br>

## Examples

```
if (sits_run_examples()) {  
  # create a SOM map  
  som_map <- sits_som_map(samples_modis_ndvi)  
  # evaluate the SOM cluster  
  som_clusters <- sits_som_evaluate_cluster(som_map)  
  # plot the SOM cluster evaluation  
  plot(som_clusters)  
}
```

---

plot.som\_map

*Plot a SOM map*

---

## Description

plots a SOM map generated by "sits\_som\_map". The plot function produces different plots based on the input data. If type is "codes", plots the vector weight for in each neuron. If type is "mapping", shows where samples are mapped.

## Usage

```
## S3 method for class 'som_map'  
plot(x, y, ..., type = "codes", band = 1)
```

## Arguments

x	Object of class "som_map".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .
type	Type of plot: "codes" for neuron weight (time series) and "mapping" for the number of samples allocated in a neuron.
band	What band will be plotted.

## Value

Called for side effects.

## Note

Please refer to the sits documentation available in [<https://e-sensing.github.io/sitsbook/>](https://e-sensing.github.io/sitsbook/) for detailed examples.

## Author(s)

Gilberto Camara, [<gilberto.camara@inpe.br>](mailto:gilberto.camara@inpe.br)

## Examples

```
if (sits_run_examples()) {  
  # create a SOM map  
  som_map <- sits_som_map(samples_modis_ndvi)  
  # plot the SOM map  
  plot(som_map)  
}
```

---

plot.torch\_model      *Plot Torch (deep learning) model*

---

## Description

Plots a deep learning model developed using torch.

## Usage

```
## S3 method for class 'torch_model'  
plot(x, y, ...)
```

## Arguments

x	Object of class "torch_model".
y	Ignored.
...	Further specifications for <a href="#">plot</a> .

## Value

A plot object produced by the ggplot2 package showing the evolution of the loss and accuracy of the model.

## Note

This code has been lifted from the "keras" package.

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

## Author(s)

Felipe Souza, <lipecaso@gmail.com>  
Rolf Simoes, <rolf.simoes@inpe.br>  
Alber Sanchez, <alber.ipia@inpe.br>



**Examples**

```

if (sits_run_examples()) {
  # Retrieve the samples for Mato Grosso
  # train a tempCNN model
  ml_model <- sits_train(samples_modis_ndvi, ml_method = sits_tempcnn)
  # plot the model
  plot(ml_model)
}

```

---

plot.uncertainty\_cube *Plot uncertainty cubes*

---

**Description**

plots a probability cube using stars

**Usage**

```

## S3 method for class 'uncertainty_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  palette = "RdYlGn",
  style = "cont",
  rev = TRUE,
  n_colors = 10,
  scale = 0.8
)

```

**Arguments**

x	Object of class "probs_image".
...	Further specifications for <a href="#">plot</a> .
tile	Tiles to be plotted.
palette	An RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
rev	Reverse the color order in the palette?
n_colors	Number of colors to be shown
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot object produced by the stars package with a map showing the uncertainty associated to each classified pixel.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # calculate uncertainty
  uncert_cube <- sits_uncertainty(probs_cube, output_dir = tempdir())
  # plot the resulting uncertainty cube
  plot(uncert_cube)
}
```

---

plot.uncertainty\_vector\_cube

*Plot uncertainty vector cubes*

---

**Description**

plots a probability cube using stars

**Usage**

```
## S3 method for class 'uncertainty_vector_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  palette = "RdYlGn",
  style = "cont",
  rev = TRUE,
  scale = 0.8
)
```

**Arguments**

x	Object of class "probs_vector_cube".
...	Further specifications for <code>plot</code> .
tile	Tile to be plotted.
palette	RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
rev	Reverse order of colors in palette?
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot containing probabilities associated to each class for each pixel.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # segment the image
  segments <- sits_segment(
    cube = cube,
    seg_fn = sits_slic(step = 5,
                      compactness = 1,
                      dist_fun = "euclidean",
                      avg_fun = "median",
                      iter = 20,
                      minarea = 10,
                      verbose = FALSE),
    output_dir = tempdir()
  )
  # classify a data cube
  probs_vector_cube <- sits_classify(
    data = segments,
    ml_model = rfor_model,
    output_dir = tempdir()
  )
  # measure uncertainty
```

```

    uncert_vector_cube <- sits_uncertainty(
      cube = probs_vector_cube,
      type = "margin",
      output_dir = tempdir()
    )
    # plot the resulting uncertainty cube
    plot(uncert_vector_cube)
  }

```

---

plot.variance\_cube      *Plot variance cubes*

---

### Description

plots a probability cube using stars

### Usage

```

## S3 method for class 'variance_cube'
plot(
  x,
  ...,
  tile = x[["tile"]][[1]],
  labels = NULL,
  palette = "YlGnBu",
  style = "cont",
  n_colors = 10,
  rev = FALSE,
  type = "map",
  scale = 0.8
)

```

### Arguments

x	Object of class "variance_cube".
...	Further specifications for <a href="#">plot</a> .
tile	Tile to be plotted.
labels	Labels to plot (optional).
palette	RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
n_colors	Number of colors to be shown
rev	Reverse order of colors in palette?
type	Type of plot ("map" or "hist")
scale	Scale to plot map (0.4 to 1.0)

**Value**

A plot containing probabilities associated to each class for each pixel.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # obtain a variance cube
  var_cube <- sits_variance(probs_cube, output_dir = tempdir())
  # plot the variance cube
  plot(var_cube)
}
```

---

plot.vector_cube	<i>Plot RGB vector data cubes</i>
------------------	-----------------------------------

---

**Description**

Plot RGB raster cube

**Usage**

```
## S3 method for class 'vector_cube'
plot(
  x,
  ...,
  band = NULL,
  red = NULL,
  green = NULL,
  blue = NULL,
  tile = x[["tile"]][[1]],
```

```
date = NULL,  
seg_color = "black",  
line_width = 1,  
palette = "RdYlGn",  
style = "cont",  
n_colors = 10,  
rev = FALSE,  
scale = 0.8  
)
```

### Arguments

x	Object of class "raster_cube".
...	Further specifications for <a href="#">plot</a> .
band	Band for plotting grey images.
red	Band for red color.
green	Band for green color.
blue	Band for blue color.
tile	Tile to be plotted.
date	Date to be plotted.
seg_color	Color to show the segment boundaries
line_width	Line width to plot the segments boundary (in pixels)
palette	An RColorBrewer palette
style	Method to process the color scale ("cont", "order", "quantile", "fisher", "jenks", "log10")
n_colors	Number of colors to be shown
rev	Reverse the color order in the palette?
scale	Scale to plot map (0.4 to 1.0)

### Value

A plot object with an RGB image or a B/W image on a color scale using the palette

### Note

To see which color palettes are supported, please run

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # Segment the cube
  segments <- sits_segment(
    cube = cube,
    output_dir = tempdir(),
    multicores = 2,
    memsize = 4
  )
  # plot NDVI band of the second date date of the data cube
  plot(segments, band = "NDVI", date = sits_timeline(cube)[1])
}

```

---

plot.xgb\_model

*Plot XGB model*


---

**Description**

Plots trees in an extreme gradient boosting model.

**Usage**

```

## S3 method for class 'xgb_model'
plot(x, ..., trees = 0:4, width = 1500, height = 1900)

```

**Arguments**

x	Object of class "xgb_model".
...	Further specifications for <a href="#">plot</a> .
trees	Vector of trees to be plotted
width	Width of the output window
height	Height of the output window

**Value**

A plot

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # Retrieve the samples for Mato Grosso
  # train an extreme gradient boosting
  xgb_model <- sits_train(samples_modis_ndvi,
    ml_method = sits_xgboost()
  )
  plot(xgb_model)
}
```

---

point\_mt\_6bands

*A time series sample with data from 2000 to 2016*

---

**Description**

A dataset containing a tibble with one time series samples in the Mato Grosso state of Brazil. The time series comes from MOD13Q1 collection 6 images.

**Usage**

```
data(point_mt_6bands)
```

**Format**

A tibble with 1 rows and 7 variables: longitude: East-west coordinate of the time series sample (WGS 84), latitude (North-south coordinate of the time series sample in WGS 84), start\_date (initial date of the time series), end\_date (final date of the time series), label (the class label associated to the sample), cube (the name of the cube associated with the data), time\_series (list containing a tibble with the values of the time series).

---

samples\_18\_rondonia\_2bands

*Samples of Amazon tropical forest biome for deforestation analysis*

---

**Description**

A sits tibble with time series samples from Brazilian Amazonia rain forest.

The labels are: "Deforestation", "Forest", "NatNonForest" and "Pasture".

The time series were extracted from the Landsat-8 BDC data cube (collection = "LC8\_30\_16D\_STK-1", tiles = "038047"). These time series comprehends a period of 12 months (25 observations) from "2018-07-12" to "2019-07-28". The extracted bands are NDVI and EVI. Cloudy values were removed and interpolated.



**Usage**

```
data("samples_l8_rondonia_2bands")
```

**Format**

A sits tibble with 160 samples.

---

samples_modis_ndvi	<i>Samples of nine classes for the state of Mato Grosso</i>
--------------------	---

---

**Description**

A dataset containing a tibble with time series samples for the Mato Grosso state in Brasil. The time series come from MOD13Q1 collection 6 images. The data set has the following classes: Cerrado(379 samples), Forest (131 samples), Pasture (344 samples), and Soy\_Corn (364 samples).

**Usage**

```
data(samples_modis_ndvi)
```

**Format**

A tibble with 1308 rows and 7 variables: longitude: East-west coordinate of the time series sample (WGS 84), latitude (North-south coordinate of the time series sample in WGS 84), start\_date (initial date of the time series), end\_date (final date of the time series), label (the class label associated to the sample), cube (the name of the cube associated with the data), time\_series (list containing a tibble with the values of the time series).

---

sits_accuracy	<i>Assess classification accuracy (area-weighted method)</i>
---------------	--

---

**Description**

This function calculates the accuracy of the classification result. For a set of time series, it creates a confusion matrix and then calculates the resulting statistics using package caret. The time series needs to be classified using [sits\\_classify](#).

Classified images are generated using [sits\\_classify](#) followed by [sits\\_label\\_classification](#). For a classified image, the function uses an area-weighted technique proposed by Olofsson et al. according to [1-3] to produce more reliable accuracy estimates at 95

In both cases, it provides an accuracy assessment of the classified, including Overall Accuracy, Kappa, User's Accuracy, Producer's Accuracy and error matrix (confusion matrix)

**Usage**

```
sits_accuracy(data, ...)

## S3 method for class 'sits'
sits_accuracy(data, ...)

## S3 method for class 'class_cube'
sits_accuracy(data, ..., validation)

## S3 method for class 'raster_cube'
sits_accuracy(data, ...)

## S3 method for class 'derived_cube'
sits_accuracy(data, ...)

## S3 method for class 'tbl_df'
sits_accuracy(data, ...)

## Default S3 method:
sits_accuracy(data, ...)
```

**Arguments**

data	Either a data cube with classified images or a set of time series
...	Specific parameters
validation	Samples for validation (see below) Only required when data is a class cube.

**Value**

A list of lists: The `error_matrix`, the `class_areas`, the unbiased estimated areas, the standard error areas, confidence interval 95 and the accuracy (user, producer, and overall), or NULL if the data is empty. A confusion matrix assessment produced by the `caret` package.

**Note**

The validation data needs to contain the following columns: "latitude", "longitude", "start\_date", "end\_date", and "label". It can be either a path to a CSV file, a sits tibble or a data frame.

**Author(s)**

Rolf Simoes, <rolf.simoese@inpe.br>  
 Alber Sanchez, <alber.ipia@inpe.br>

**References**

[1] Olofsson, P., Foody, G.M., Stehman, S.V., Woodcock, C.E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, 129, pp.122-131.

[2] Olofsson, P., Foody G.M., Herold M., Stehman, S.V., Woodcock, C.E., Wulder, M.A. (2014) Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, pp. 42-57.

[3] FAO, Map Accuracy Assessment and Area Estimation: A Practical Guide. National forest monitoring assessment working paper No.46/E, 2016.

## Examples

```
if (sits_run_examples()) {
  # show accuracy for a set of samples
  train_data <- sits_sample(samples_modis_ndvi, frac = 0.5)
  test_data <- sits_sample(samples_modis_ndvi, frac = 0.5)
  rfor_model <- sits_train(train_data, sits_rfor())
  points_class <- sits_classify(
    data = test_data, ml_model = rfor_model
  )
  acc <- sits_accuracy(points_class)

  # show accuracy for a data cube classification
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # obtain the ground truth for accuracy assessment
  ground_truth <- system.file("extdata/samples/samples_sinop_crop.csv",
    package = "sits"
  )
  # make accuracy assessment
  as <- sits_accuracy(label_cube, validation = ground_truth)
}
```

**Description**

Apply a named expression to a sits cube or a sits tibble to be evaluated and generate new bands (indices). In the case of sits cubes, it materializes a new band in output\_dir using gdalcubes.

**Usage**

```
sits_apply(data, ...)

## S3 method for class 'sits'
sits_apply(data, ...)

## S3 method for class 'raster_cube'
sits_apply(
  data,
  ...,
  window_size = 3L,
  memsize = 4L,
  multicores = 2L,
  normalized = TRUE,
  output_dir,
  progress = FALSE
)

## S3 method for class 'derived_cube'
sits_apply(data, ...)

## Default S3 method:
sits_apply(data, ...)
```

**Arguments**

data	Valid sits tibble or cube
...	Named expressions to be evaluated (see details).
window_size	An odd number representing the size of the sliding window of sits kernel functions used in expressions (for a list of supported kernel functions, please see details).
memsize	Memory available for classification (in GB).
multicores	Number of cores to be used for classification.
normalized	Produce normalized band?
output_dir	Directory where files will be saved.
progress	Show progress bar?

**Details**

sits\_apply() allow any valid R expression to compute new bands. Use R syntax to pass an expression to this function. Besides arithmetic operators, you can use virtually any R function that

can be applied to elements of a matrix (functions that are unaware of matrix sizes, e.g. `sqrt()`, `sin()`, `log()`).

Also, `sits_apply()` accepts a predefined set of kernel functions (see below) that can be applied to pixels considering its neighborhood. `sits_apply()` considers a neighborhood of a pixel as a set of pixels equidistant to it (including itself) according to the Chebyshev distance. This neighborhood form a square window (also known as kernel) around the central pixel (Moore neighborhood). Users can set the `window_size` parameter to adjust the size of the kernel window. The image is conceptually mirrored at the edges so that neighborhood including a pixel outside the image is equivalent to take the 'mirrored' pixel inside the edge.

`sits_apply()` applies a function to the kernel and its result is assigned to a corresponding central pixel on a new matrix. The kernel slides throughout the input image and this process generates an entire new matrix, which is returned as a new band to the cube. The kernel functions ignores any NA values inside the kernel window. Central pixel is NA just only all pixels in the window are NA.

By default, the indexes generated by the `sits_apply()` function are normalized between -1 and 1, scaled by a factor of 0.0001. Normalized indexes are saved as INT2S (Integer with sign). If the normalized parameter is FALSE, no scaling factor will be applied and the index will be saved as FLT4S (Float with sign).

### Value

A sits tibble or a sits cube with new bands, produced according to the requested expression.

### Summarizing kernel functions

- `w_median()`: returns the median of the neighborhood's values.
- `w_sum()`: returns the sum of the neighborhood's values.
- `w_mean()`: returns the mean of the neighborhood's values.
- `w_sd()`: returns the standard deviation of the neighborhood's values.
- `w_min()`: returns the minimum of the neighborhood's values.
- `w_max()`: returns the maximum of the neighborhood's values.
- `w_var()`: returns the variance of the neighborhood's values.
- `w_modal()`: returns the modal of the neighborhood's values.

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Carvalho, <felipe.carvalho@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

### Examples

```
if (sits_run_examples()) {
  # Get a time series
  # Apply a normalization function

  point2 <-
```

```

sits_select(point_mt_6bands, "NDVI") |>
sits_apply(NDVI_norm = (NDVI - min(NDVI)) / (max(NDVI) - min(NDVI)))

# Example of generation texture band with variance
# Create a data cube from local files
data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
cube <- sits_cube(
  source = "BDC",
  collection = "MOD13Q1-6",
  data_dir = data_dir
)

# Generate a texture images with variance in NDVI images
cube_texture <- sits_apply(
  data = cube,
  NDVITEXTURE = w_median(NDVI),
  window_size = 5,
  output_dir = tempdir()
)
}

```

---

sits\_as\_sf

*Return a sits\_tibble or raster\_cube as an sf object.*


---

## Description

Return a sits\_tibble or raster\_cube as an sf object.

## Usage

```

sits_as_sf(data, ..., as_crs = NULL)

## S3 method for class 'sits'
sits_as_sf(data, ..., crs = "EPSG:4326", as_crs = NULL)

## S3 method for class 'raster_cube'
sits_as_sf(data, ..., as_crs = NULL)

```

## Arguments

data	A sits tibble or sits cube.
...	Additional parameters.
as_crs	Output coordinate reference system.
crs	Input coordinate reference system.

## Value

An sf object of point or polygon geometry.

**Author(s)**

Felipe Carvalho, <felipe.carvalho@inpe.br>

Alber Sanchez, <alber.ipia@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # convert sits tibble to an sf object (point)  
  sf_object <- sits_as_sf(cerrado_2classes)  
  
  # convert sits cube to an sf object (polygon)  
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")  
  cube <- sits_cube(  
    source = "BDC",  
    collection = "MOD13Q1-6",  
    data_dir = data_dir  
  )  
  sf_object <- sits_as_sf(cube)  
}
```

---

sits\_bands

*Get the names of the bands*

---

**Description**

Finds the names of the bands of a set of time series or of a data cube

**Usage**

```
sits_bands(x)  
  
## S3 method for class 'sits'  
sits_bands(x)  
  
## S3 method for class 'raster_cube'  
sits_bands(x)  
  
## S3 method for class 'patterns'  
sits_bands(x)  
  
## S3 method for class 'sits_model'  
sits_bands(x)  
  
## Default S3 method:  
sits_bands(x)  
  
sits_bands(x) <- value
```

```
## S3 replacement method for class 'sits'
sits_bands(x) <- value

## S3 replacement method for class 'raster_cube'
sits_bands(x) <- value

## Default S3 replacement method:
sits_bands(x) <- value
```

### Arguments

x	Valid sits tibble (time series or a cube)
value	New value for the bands

### Value

A vector with the names of the bands.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>  
 Rolf Simoes, <rolf.simoes@inpe.br>

### Examples

```
if (sits_run_examples()) {
  # Create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # Get the bands from a data cube
  bands <- sits_bands(cube)
  # Get the bands from a sits tibble
  bands <- sits_bands(samples_modis_ndvi)
  # Get the bands from patterns
  bands <- sits_bands(sits_patterns(samples_modis_ndvi))
  # Get the bands from ML model
  rf_model <- sits_train(samples_modis_ndvi, sits_rfor())
  bands <- sits_bands(rf_model)
  # Set the bands for a SITS time series
  sits_bands(samples_modis_ndvi) <- "NDVI2"
  # Set the bands for a SITS cube
  sits_bands(cube) <- "NDVI2"
}
```



---

sits_bbox	<i>Get the bounding box of the data</i>
-----------	---

---

### Description

Obtain a vector of limits (either on lat/long for time series or in projection coordinates in the case of cubes)

### Usage

```
sits_bbox(data, crs = "EPSG:4326", as_crs = NULL)

## S3 method for class 'sits'
sits_bbox(data, crs = "EPSG:4326", as_crs = NULL)

## S3 method for class 'raster_cube'
sits_bbox(data, crs = "EPSG:4326", as_crs = NULL)

## S3 method for class 'tbl_df'
sits_bbox(data, crs = "EPSG:4326", as_crs = NULL)

## Default S3 method:
sits_bbox(data, crs = "EPSG:4326", as_crs = NULL)
```

### Arguments

data	samples (class "sits") or cube.
crs	CRS of the samples points (single char)
as_crs	CRS to project the resulting bbox.

### Value

A bbox.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>  
Rolf Simoes, <rolf.simoes@inpe.br>

### Examples

```
if (sits_run_examples()) {
  # get the bbox of a set of samples
  sits_bbox(samples_modis_ndvi)
  # get the bbox of a cube in WGS84
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
```

```

        source = "BDC",
        collection = "MOD13Q1-6",
        data_dir = data_dir
    )
    sits_bbox(cube, as_crs = "EPSG:4326")
}

```

---

sits\_classify

*Classify time series or data cubes*


---

### Description

This function classifies a set of time series or data cube given a trained model prediction model created by [sits\\_train](#).

SITS supports the following models: (a) support vector machines: [sits\\_svm](#); (b) random forests: [sits\\_rfor](#); (c) extreme gradient boosting: [sits\\_xgboost](#); (d) multi-layer perceptrons: [sits\\_mlp](#); (e) 1D CNN: [sits\\_tempcnn](#); (f) deep residual networks: [sits\\_resnet](#); (g) self-attention encoders: [sits\\_lighttae](#).

### Usage

```

sits_classify(
  data,
  ml_model,
  ...,
  filter_fn = NULL,
  multicores = 2L,
  progress = TRUE
)

## S3 method for class 'sits'
sits_classify(
  data,
  ml_model,
  ...,
  filter_fn = NULL,
  impute_fn = impute_linear(),
  multicores = 2L,
  gpu_memory = 16,
  progress = TRUE
)

## S3 method for class 'raster_cube'
sits_classify(
  data,
  ml_model,
  ...,

```

```

    roi = NULL,
    filter_fn = NULL,
    impute_fn = impute_linear(),
    start_date = NULL,
    end_date = NULL,
    memsize = 8L,
    multicores = 2L,
    gpu_memory = 16,
    output_dir,
    version = "v1",
    verbose = FALSE,
    progress = TRUE
)

## S3 method for class 'derived_cube'
sits_classify(data, ml_model, ...)

## S3 method for class 'tbl_df'
sits_classify(data, ml_model, ...)

## S3 method for class 'segs_cube'
sits_classify(
  data,
  ml_model,
  ...,
  roi = NULL,
  filter_fn = NULL,
  impute_fn = impute_linear(),
  start_date = NULL,
  end_date = NULL,
  memsize = 8L,
  multicores = 2L,
  gpu_memory = 16,
  output_dir,
  version = "v1",
  n_sam_pol = NULL,
  verbose = FALSE,
  progress = TRUE
)

## Default S3 method:
sits_classify(data, ml_model, ...)

```

### Arguments

<code>data</code>	Data cube (tibble of class "raster_cube")
<code>ml_model</code>	R model trained by <code>sits_train</code> (closure of class "sits_model")
<code>...</code>	Other parameters for specific functions.

<code>filter_fn</code>	Smoothing filter to be applied - optional (closure containing object of class "function").
<code>multicores</code>	Number of cores to be used for classification (integer, min = 1, max = 2048).
<code>progress</code>	Logical: Show progress bar?
<code>impute_fn</code>	Imputation function to remove NA.
<code>gpu_memory</code>	Memory available in GPU in GB (default = 16)
<code>roi</code>	Region of interest (either an sf object, shapefile, or a numeric vector with named XY values ("xmin", "xmax", "ymin", "ymax") or named lat/long values ("lon_min", "lat_min", "lon_max", "lat_max")).
<code>start_date</code>	Start date for the classification (Date in YYYY-MM-DD format).
<code>end_date</code>	End date for the classification (Date in YYYY-MM-DD format).
<code>memszie</code>	Memory available for classification in GB (integer, min = 1, max = 16384).
<code>output_dir</code>	Valid directory for output file. (character vector of length 1).
<code>version</code>	Version of the output (character vector of length 1).
<code>verbose</code>	Logical: print information about processing time?
<code>n_sam_pol</code>	Number of time series per segment to be classified (integer, min = 10, max = 50).

**Value**

Time series with predicted labels for each point (tibble of class "sits") or a data cube with probabilities for each class (tibble of class "probs\_cube").

**Note**

The `roi` parameter defines a region of interest. It can be an `sf_object`, a shapefile, or a bounding box vector with named XY values (`xmin`, `xmax`, `ymin`, `ymax`) or named lat/long values (`lon_min`, `lon_max`, `lat_min`, `lat_max`).

Parameter `filter_fn` parameter specifies a smoothing filter to be applied to each time series for reducing noise. Currently, options are Savitzky-Golay (see [sits\\_sgolay](#)) and Whittaker (see [sits\\_whittaker](#)) filters.

Parameter `memszie` controls the amount of memory available for classification, while `multicores` defines the number of cores used for processing. We recommend using as much memory as possible.

When using a GPU for deep learning, `gpu_memory` indicates the memory of available in the graphics card. It is not possible to have an exact idea of the size of Deep Learning models in GPU memory, as the complexity of the model and factors such as CUDA Context increase the size of the model in memory. Therefore, we recommend that you leave at least 1GB free on the video card to store the Deep Learning model that will be used.

For classifying vector data cubes created by [sits\\_segment](#), `n_sam_pol` controls is the number of time series to be classified per segment.

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # Example of classification of a time series
  # Retrieve the samples for Mato Grosso
  # train a random forest model
  rf_model <- sits_train(samples_modis_ndvi, ml_method = sits_rfor)

  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = c("NDVI"))
  point_class <- sits_classify(
    data = point_ndvi, ml_model = rf_model
  )
  plot(point_class)

  # Example of classification of a data cube
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube,
    ml_model = rf_model,
    output_dir = tempdir(),
    version = "ex_classify"
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir(),
    version = "ex_classify"
  )
  # plot the classified image
  plot(label_cube)
  # segmentation
  # segment the image
  segments <- sits_segment(
    cube = cube,
    seg_fn = sits_slic(step = 5,
                      compactness = 1,
                      dist_fun = "euclidean",
                      avg_fun = "median",
                      iter = 50,
                      minarea = 10,
```

```

        verbose = FALSE
      ),
      output_dir = tempdir()
    )
    # Create a classified vector cube
    probs_segs <- sits_classify(
      data = segments,
      ml_model = rf_model,
      output_dir = tempdir(),
      multicores = 4,
      version = "segs"
    )
    # Create a labelled vector cube
    class_segs <- sits_label_classification(
      cube = probs_segs,
      output_dir = tempdir(),
      multicores = 2,
      memsize = 4,
      version = "segs_classify"
    )
    # plot class_segs
    plot(class_segs)
  }

```

---

sits\_clean

*Cleans a classified map using a local window*


---

### Description

Applies a modal function to clean up possible noisy pixels keeping the most frequently values within the neighborhood. In a tie, the first value of the vector is considered.

### Usage

```

sits_clean(
  cube,
  window_size = 5L,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1-clean",
  progress = TRUE
)

## S3 method for class 'class_cube'
sits_clean(
  cube,
  window_size = 5L,

```

```
    memsize = 4L,  
    multicores = 2L,  
    output_dir,  
    version = "v1-clean",  
    progress = TRUE  
  )  
  
## S3 method for class 'raster_cube'  
sits_clean(  
  cube,  
  window_size = 5L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1-clean",  
  progress = TRUE  
)  
  
## S3 method for class 'derived_cube'  
sits_clean(  
  cube,  
  window_size = 5L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1-clean",  
  progress = TRUE  
)  
  
## Default S3 method:  
sits_clean(  
  cube,  
  window_size = 5L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1-clean",  
  progress = TRUE  
)
```

### Arguments

cube	Classified data cube (tibble of class "class_cube").
window_size	An odd integer representing the size of the sliding window of the modal function (min = 1, max = 15).
memsize	Memory available for classification in GB (integer, min = 1, max = 16384).
multicores	Number of cores to be used for classification (integer, min = 1, max = 2048).
output_dir	Valid directory for output file. (character vector of length 1).

version            Version of the output file (character vector of length 1)  
 progress          Logical: Show progress bar?

**Value**

A tibble with an classified map (class = "class\_cube").

**Author(s)**

Felipe Carvalho, <felipe.carvalho@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  rf_model <- sits_train(samples_modis_ndvi, ml_method = sits_rfor)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube,
    ml_model = rf_model,
    output_dir = tempdir()
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # apply a mode function in the labelled cube
  clean_cube <- sits_clean(
    cube = label_cube,
    window_size = 5,
    output_dir = tempdir(),
    multicores = 1
  )
}
```

---

sits\_cluster\_clean      *Removes labels that are minority in each cluster.*

---

**Description**

Takes a tibble with time series that has an additional 'cluster' produced by `link[sits]{sits_cluster_dendro()}` and removes labels that are minority in each cluster.



**Usage**

```
sits_cluster_clean(samples)
```

**Arguments**

samples           Tibble with set of time series with additional cluster information produced by `link[sits]{sits_cluster_dendro()}`

**Value**

Tibble with time series (class "sits")

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  clusters <- sits_cluster_dendro(cerrado_2classes)  
  freq1 <- sits_cluster_frequency(clusters)  
  freq1  
  clean_clusters <- sits_cluster_clean(clusters)  
  freq2 <- sits_cluster_frequency(clean_clusters)  
  freq2  
}
```

---

sits\_cluster\_dendro    *Find clusters in time series samples*

---

**Description**

These functions support hierarchical agglomerative clustering in sits. They provide support from creating a dendrogram and using it for cleaning samples.

`link[sits]{sits_cluster_dendro()}` takes a tibble with time series and produces a sits tibble with an added "cluster" column. The function first calculates a dendrogram and obtains a validity index for best clustering using the adjusted Rand Index. After cutting the dendrogram using the chosen validity index, it assigns a cluster to each sample.

`link[sits]{sits_cluster_frequency()}` computes the contingency table between labels and clusters and produces a matrix. Its input is a tibble produced by `link[sits]{sits_cluster_dendro()}`.

`link[sits]{sits_cluster_clean()}` takes a tibble with time series that has an additional 'cluster' produced by `link[sits]{sits_cluster_dendro()}` and removes labels that are minority in each cluster.

**Usage**

```
sits_cluster_dendro(
  samples,
  bands = NULL,
  dist_method = "dtw_basic",
  linkage = "ward.D2",
  k = NULL,
  palette = "RdYlGn"
)

## S3 method for class 'sits'
sits_cluster_dendro(
  samples,
  bands = NULL,
  dist_method = "dtw_basic",
  linkage = "ward.D2",
  k = NULL,
  palette = "RdYlGn",
  ...
)

## Default S3 method:
sits_cluster_dendro(samples, ...)
```

**Arguments**

<code>samples</code>	Tibble with input set of time series (class "sits").
<code>bands</code>	Bands to be used in the clustering (character vector)
<code>dist_method</code>	One of the supported distances (single char vector) "dtw": DTW with a Sakoe-Chiba constraint. "dtw2": DTW with L2 norm and Sakoe-Chiba constraint. "dtw_basic": A faster DTW with less functionality. "lbk": Keogh's lower bound for DTW. "lbi": Lemire's lower bound for DTW.
<code>linkage</code>	Agglomeration method to be used (single char vector) One of "ward.D", "ward.D2", "single", "complete", "average", "mcquitty", "median" or "centroid".
<code>k</code>	Desired number of clusters (overrides default value)
<code>palette</code>	Color palette as per 'grDevices::hcl.pals()' function.
<code>...</code>	Additional parameters to be passed to dtwclust::tsclust() function.

**Value**

Tibble with "cluster" column (class "sits\_cluster").

**Note**

Please refer to the sits documentation available in <<https://e-sensing.github.io/sitsbook/>> for detailed examples.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**References**

"dtwclust" package (<https://CRAN.R-project.org/package=dtwclust>)

**Examples**

```
if (sits_run_examples()) {  
  # default  
  clusters <- sits_cluster_dendro(cerrado_2classes)  
  # with parameters  
  clusters <- sits_cluster_dendro(cerrado_2classes,  
                                bands = "NDVI", k = 5)  
}
```

---

sits\_cluster\_frequency

*Show label frequency in each cluster produced by dendrogram analysis*

---

**Description**

Show label frequency in each cluster produced by dendrogram analysis

**Usage**

```
sits_cluster_frequency(samples)
```

**Arguments**

**samples**      Tibble with input set of time series with additional cluster information produced by `link[sits]{sits_cluster_dendro}`.

**Value**

A matrix containing frequencies of labels in clusters.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  clusters <- sits_cluster_dendro(cerrado_2classes)  
  freq <- sits_cluster_frequency(clusters)  
  freq  
}
```

---

**sits\_colors***Function to retrieve sits color table*

---

**Description**

Returns a color table

**Usage**

```
sits_colors(legend = NULL)
```

**Arguments**

legend            One of the accepted legends in sits

**Value**

A tibble with color names and values

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # return the names of all colors supported by SITS  
  sits_colors()  
}
```

---

sits\_colors\_qgis      *Function to save color table as QML style for data cube*

---

### Description

Saves a color table associated to a classified data cube as a QGIS style file

### Usage

```
sits_colors_qgis(cube, file)
```

### Arguments

cube	a classified data cube
file	a QGIS style file to be written to

### Value

No return, called for side effects

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

### Examples

```
if (sits_run_examples()) {
  data_dir <- system.file("extdata/raster/classif", package = "sits")
  ro_class <- sits_cube(
    source = "MPC",
    collection = "SENTINEL-2-L2A",
    data_dir = data_dir,
    parse_info = c("X1", "X2", "tile", "start_date", "end_date",
                  "band", "version"),
    bands = "class",
    labels = c(
      "1" = "Clear_Cut_Burned_Area",
      "2" = "Clear_Cut_Bare_Soil",
      "3" = "Clear_Cut_Vegetation",
      "4" = "Forest")
  )
  qml_file <- paste0(tempdir(), "/qgis.qml")
  sits_colors_qgis(ro_class, qml_file)
}
```

---

sits\_colors\_reset      *Function to reset sits color table*

---

**Description**

Resets the color table

**Usage**

```
sits_colors_reset()
```

**Value**

No return, called for side effects

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # reset the default colors supported by SITS  
  sits_colors_reset()  
}
```

---

sits\_colors\_set      *Function to set sits color table*

---

**Description**

Includes new colors in the SITS color sets. If the colors exist, replace them with the new HEX value. Optionally, the new colors can be associated to a legend. In this case, the new legend name should be informed. The colors parameter should be a data.frame or a tibble with name and HEX code. Colour names should be one character string only. Composite names need to be combined with underscores (e.g., use "Snow\_and\_Ice" and not "Snow and Ice").

This function changes the global sits color table and the global set of sits color legends. To undo these effects, please use "sits\_colors\_reset()".

**Usage**

```
sits_colors_set(colors, legend = NULL)
```

**Arguments**

colors	New color table (a tibble or data.frame with name and HEX code)
legend	Legend associated to the color table (optional)

**Value**

A modified sits color table (invisible)

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # Define a color table based on the Anderson Land Classification System
  us_nlcd <- tibble::tibble(name = character(), color = character())
  us_nlcd <- us_nlcd |>
    tibble::add_row(name = "Urban_Built_Up", color = "#85929E") |>
    tibble::add_row(name = "Agricultural_Land", color = "#F0B27A") |>
    tibble::add_row(name = "Rangeland", color = "#F1C40F") |>
    tibble::add_row(name = "Forest_Land", color = "#27AE60") |>
    tibble::add_row(name = "Water", color = "#2980B9") |>
    tibble::add_row(name = "Wetland", color = "#D4E6F1") |>
    tibble::add_row(name = "Barren_Land", color = "#FDEBD0") |>
    tibble::add_row(name = "Tundra", color = "#EBDEF0") |>
    tibble::add_row(name = "Snow_and_Ice", color = "#F7F9F9")

  # Load the color table into `sits`
  sits_colors_set(colors = us_nlcd, legend = "US_NLCD")

  # Show the new color table used by sits
  sits_colors_show("US_NLCD")

  # Change colors in the sits global color table
  # First show the default colors for the UMD legend
  sits_colors_show("UMD")
  # Then change some colors associated to the UMD legend
  mycolors <- tibble::tibble(name = character(), color = character())
  mycolors <- mycolors |>
    tibble::add_row(name = "Savannas", color = "#F8C471") |>
    tibble::add_row(name = "Grasslands", color = "#ABEBC6")
  sits_colors_set(colors = mycolors)
  # Notice that the UMD colors change
  sits_colors_show("UMD")
  # Reset the color table
  sits_colors_reset()
  # Show the default colors for the UMD legend
  sits_colors_show("UMD")
}

```

**Description**

Shows the default SITS colors

**Usage**

```
sits_colors_show(legend = NULL, font_family = "sans")
```

**Arguments**

legend	One of the accepted legends in sits
font_family	A font family loaded in SITS

**Value**

no return, called for side effects

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # show the colors supported by SITS
  sits_colors_show()
}
```

---

sits\_combine\_predictions

*Estimate ensemble prediction based on list of probs cubes*

---

**Description**

Calculate an ensemble predictor based a list of probability cubes. The function combines the output of two or more classifier to derive a value which is based on weights assigned to each model. The supported types of ensemble predictors are 'average' and 'uncertainty'.

**Usage**

```
sits_combine_predictions(
  cubes,
  type = "average",
  ...,
  memsize = 8L,
  multicores = 2L,
  output_dir,
  version = "v1"
```



```

)

## S3 method for class 'average'
sits_combine_predictions(
  cubes,
  type = "average",
  ...,
  weights = NULL,
  memsize = 8L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## S3 method for class 'uncertainty'
sits_combine_predictions(
  cubes,
  type = "uncertainty",
  ...,
  uncert_cubes,
  memsize = 8L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## Default S3 method:
sits_combine_predictions(cubes, type, ...)

```

### Arguments

cubes	List of probability data cubes (class "probs_cube")
type	Method to measure uncertainty. One of "average" or "uncertainty"
...	Parameters for specific functions.
memsize	Memory available for classification in GB (integer, min = 1, max = 16384).
multicores	Number of cores to be used for classification (integer, min = 1, max = 2048).
output_dir	Valid directory for output file. (character vector of length 1).
version	Version of the output (character vector of length 1).
weights	Weights for averaging (numeric vector).
uncert_cubes	Uncertainty cubes to be used as local weights when type = "uncertainty" is selected (list of tibbles with class "uncertainty_cube")

### Value

A combined probability cube (tibble of class "probs\_cube").

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify a data cube using rfor model
  probs_rfor_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir(),
    version = "rfor"
  )
  # create an XGBoost model
  svm_model <- sits_train(samples_modis_ndvi, sits_svm())
  # classify a data cube using SVM model
  probs_svm_cube <- sits_classify(
    data = cube, ml_model = svm_model, output_dir = tempdir(),
    version = "svm"
  )
  # create a list of predictions to be combined
  pred_cubes <- list(probs_rfor_cube, probs_svm_cube)
  # combine predictions
  comb_probs_cube <- sits_combine_predictions(
    pred_cubes,
    output_dir = tempdir()
  )
  # plot the resulting combined prediction cube
  plot(comb_probs_cube)
}

```

---

sits\_confidence\_sampling

*Suggest high confidence samples to increase the training set.*

---

**Description**

Suggest points for increasing the training set. These points are labelled with high confidence so they can be added to the training set. They need to have a satisfactory margin of confidence to be selected. The input is a probability cube. For each label, the algorithm finds out location where the machine learning model has high confidence in choosing this label compared to all others. The algorithm

also considers a minimum distance between new labels, to minimize spatial autocorrelation effects. This function is best used in the following context: 1. Select an initial set of samples. 2. Train a machine learning model. 3. Build a data cube and classify it using the model. 4. Run a Bayesian smoothing in the resulting probability cube. 5. Perform confidence sampling.

The Bayesian smoothing procedure will reduce the classification outliers and thus increase the likelihood that the resulting pixels will provide good quality samples for each class.

## Usage

```
sits_confidence_sampling(
  probs_cube,
  n = 20L,
  min_margin = 0.9,
  sampling_window = 10L
)
```

## Arguments

<code>probs_cube</code>	A smoothed probability cube. See <a href="#">sits_classify</a> and <a href="#">sits_smooth</a> .
<code>n</code>	Number of suggested points per class.
<code>min_margin</code>	Minimum margin of confidence to select a sample
<code>sampling_window</code>	Window size for collecting points (in pixels). The minimum window size is 10.

## Value

A tibble with longitude and latitude in WGS84 with locations which have high uncertainty and meet the minimum distance criteria.

## Author(s)

Alber Sanchez, <alber.ipia@inpe.br>  
 Rolf Simoes, <rolf.simoes@inpe.br>  
 Felipe Carvalho, <felipe.carvalho@inpe.br>  
 Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```
if (sits_run_examples()) {
  # create a data cube
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # build a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, ml_method = sits_rfor())
}
```

```

# classify the cube
probs_cube <- sits_classify(
  data = cube, ml_model = rfor_model, output_dir = tempdir()
)
# obtain a new set of samples for active learning
# the samples are located in uncertain places
new_samples <- sits_confidence_sampling(probs_cube)
}

```

---

sits\_config

*Configure parameters for sits package*


---

## Description

These functions load and show sits configurations.

The ‘sits’ package uses a configuration file that contains information on parameters required by different functions. This includes information about the image collections handled by ‘sits’.

sits\_config() loads the default configuration file and the user provided configuration file. The final configuration is obtained by overriding the options by the values provided by the user.

## Usage

```
sits_config(config_user_file = NULL)
```

## Arguments

```
config_user_file
  YAML user configuration file (character vector of a file with "yaml" extension)
```

## Details

Users can provide additional configuration files, by specifying the location of their file in the environmental variable SITS\_CONFIG\_USER\_FILE or as parameter to this function.

To see the key entries and contents of the current configuration values, use `link[sits]{sits_config_show()}`.

## Value

Called for side effects

## Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

## Examples

```

yaml_user_file <- system.file("extdata/config_user_example.yaml",
  package = "sits")
sits_config(config_user_file = yaml_user_file)

```

---

sits_config_show	<i>Show current sits configuration</i>
------------------	--

---

**Description**

Prints the current sits configuration options. To show specific configuration options for a source, a collection, or a palette, users can inform the corresponding keys to source and collection.

**Usage**

```
sits_config_show(source = NULL, collection = NULL)
```

**Arguments**

source	Data source (character vector).
collection	Collection (character vector).

**Value**

No return value, called for side effects.

**Examples**

```
sits_config_show(source = "BDC")
sits_config_show(source = "BDC", collection = "CBERS-WFI-16D")
```

---

sits_cube	<i>Create data cubes from image collections</i>
-----------	---

---

**Description**

Creates a data cube based on spatial and temporal restrictions in collections available in cloud services or local repositories. The following cloud providers are supported, based on the STAC protocol: Amazon Web Services (AWS), Brazil Data Cube (BDC), Digital Earth Africa (DEAFRICA), Microsoft Planetary Computer (MPC), Nasa Harmonized Landsat/Sentinel (HLS), USGS Landsat (USGS), and Swiss Data Cube (SDC). Data cubes can also be created using local files.

**Usage**

```
sits_cube(source, collection, ...)
```

```
## S3 method for class 'sar_cube'
sits_cube(
  source,
  collection,
  ...,
```

```
orbit = "ascending",
bands = NULL,
tiles = NULL,
roi = NULL,
start_date = NULL,
end_date = NULL,
platform = NULL,
multicores = 2,
progress = TRUE
)

## S3 method for class 'stac_cube'
sits_cube(
  source,
  collection,
  ...,
  bands = NULL,
  tiles = NULL,
  roi = NULL,
  start_date = NULL,
  end_date = NULL,
  platform = NULL,
  multicores = 2,
  progress = TRUE
)

## S3 method for class 'local_cube'
sits_cube(
  source,
  collection,
  ...,
  data_dir,
  vector_dir = NULL,
  tiles = NULL,
  bands = NULL,
  vector_band = NULL,
  start_date = NULL,
  end_date = NULL,
  labels = NULL,
  parse_info = NULL,
  version = "v1",
  delim = "_",
  multicores = 2L,
  progress = TRUE
)
```

**Arguments**

source	Data source (one of "AWS", "BDC", "DEAFRICA", "MPC", "SDC", "USGS" - character vector of length 1).
collection	Image collection in data source (character vector of length 1). To find out the supported collections, use <code>sits_list_collections()</code> .
...	Other parameters to be passed for specific types.
orbit	Orbit name ("ascending", "descending") for SAR cubes.
bands	Spectral bands and indices to be included in the cube (optional - character vector). Use <code>sits_list_collections()</code> to find out the bands available for each collection.
tiles	Tiles from the collection to be included in the cube (see details below) (character vector of length 1).
roi	Region of interest (either an sf object, shapefile, or a numeric vector with named XY values ("xmin", "xmax", "ymin", "ymax") or named lat/long values ("lon_min", "lat_min", "lon_max", "lat_max")).
start_date, end_date	Initial and final dates to include images from the collection in the cube (optional). (Date in YYYY-MM-DD format).
platform	Optional parameter specifying the platform in case of collections that include more than one satellite (character vector of length 1).
multicores	Number of workers for parallel processing (integer, min = 1, max = 2048).
progress	Logical: show a progress bar?
data_dir	Local directory where images are stored (for local cubes - character vector of length 1).
vector_dir	Local director where vector files are stored (for local vector cubes - character vector of length 1).
vector_band	Band for vector cube ("segments", "probs", "class")
labels	Labels associated to the classes (Named character vector for cubes of classes "probs_cube" or "class_cube").
parse_info	Parsing information for local files (for local cubes - character vector).
version	Version of the classified and/or labelled files. (for local cubes - character vector of length 1).
delim	Delimiter for parsing local files (single character)

**Value**

A tibble describing the contents of a data cube.

**Note**

To create cubes from cloud providers, users need to inform:

1. source: One of "AWS", "BDC", "DEAFRICA", "HLS", "MPC", "SDC" or "USGS";

2. `collection`: Collection available in the cloud provider. Use `sits_list_collections()` to see which collections are supported;
3. `tiles`: A set of tiles defined according to the collection tiling grid;
4. `roi`: Region of interest. Either a named vector (`"lon_min", "lat_min", "lon_max", "lat_max"`) in WGS84, a `sfc` or `sf` object from `sf` package in WGS84 projection.

Either `tiles` or `roi` must be informed. The parameters `bands`, `start_date`, and `end_date` are optional for cubes created from cloud providers.

GeoJSON geometries (RFC 7946) and shapefiles should be converted to `sf` objects before being used to define a region of interest. This parameter does not crop a region; it only selects images that intersect the `roi`.

To create a cube from local files, users need to inform:

1. `source`: Provider from where the data has been downloaded (e.g, "BDC");
2. `collection`: Collection where the data has been extracted from. (e.g., "SENTINEL-2-L2A" for the Sentinel-2 MPC collection level 2A);
3. `data_dir`: Local directory where images are stored.
4. `parse_info`: Parsing information for files. Default is `c("X1", "X2", "tile", "band", "date")`.
5. `delim`: Delimiter character for parsing files. Default is `"_"`.

To create a cube from local files, all images should have the same spatial resolution and projection and each file should contain a single image band for a single date. Files can belong to different tiles of a spatial reference system and file names need to include tile, date, and band information. For example: `"CBERS-4_WFI_022024_B13_2018-02-02.tif"` and `"SENTINEL-2_MSI_20LKP_B02_2018-07-18.jp2"` are accepted names. The user has to provide parsing information to allow `sits` to extract values of tile, band, and date. In the examples above, the parsing info is `c("X1", "X2", "tile", "band", "date")` and the delimiter is `"_"`, which are the default values.

It is also possible to create result cubes for these are local files produced by classification or post-classification algorithms. In this case, more parameters that are required (see below). The parameter `parse_info` is specified differently, as follows:

1. `band`: Band name associated to the type of result. Use `"probs"`, for probability cubes produced by `sits_classify()`; `"bayes"`, for smoothed cubes produced by `sits_smooth()`; `"segments"`, for vector cubes produced by `sits_segment()`; `"entropy"` when using `sits_uncertainty()`, and `"class"` for cubes produced by `sits_label_classification()`;
2. `labels`: Labels associated to the classification results;
3. `parse_info`: File name parsing information to deduce the values of `"tile"`, `"start_date"`, `"end_date"` from the file name. Default is `c("X1", "X2", "tile", "start_date", "end_date", "band")`. Unlike non-classified image files, cubes with results have both `"start_date"` and `"end_date"`.

In MPC, `sits` can access are two open data collections: `"SENTINEL-2-L2A"` for Sentinel-2/2A images, and `"LANDSAT-C2-L2"` for the Landsat-4/5/7/8/9 collection. (`requester-pays`) and `"SENTINEL-S2-L2A-COGS"` (open data).

Sentinel-2/2A level 2A files in MPC are organized by sensor resolution. The bands in 10m resolution are `"B02"`, `"B03"`, `"B04"`, and `"B08"`. The 20m bands are `"B05"`, `"B06"`, `"B07"`, `"B8A"`, `"B11"`, and `"B12"`. Bands `"B01"` and `"B09"` are available at 60m resolution. The `"CLOUD"` band is also available.



All Landsat-4/5/7/8/9 images in MPC have bands with 30 meter resolution. To account for differences between the different sensors, Landsat bands in this collection have been renamed "BLUE", "GREEN", "RED", "NIR08", "SWIR16" and "SWIR22". The "CLOUD" band is also available.

In AWS, there are two types of collections: open data and requester-pays. Currently, sits supports collection "SENTINEL-2-L2A" (open data) and LANDSAT-C2-L2 (requester-pays). There is no need to provide AWS credentials to access open data collections. For requester-pays data, users need to provide their access codes as environment variables, as follows: `Sys.setenv(AWS_ACCESS_KEY_ID = <your_access_key>, AWS_SECRET_ACCESS_KEY = <your_secret_access_key>)`

Sentinel-2/2A level 2A files in AWS are organized by sensor resolution. The AWS bands in 10m resolution are "B02", "B03", "B04", and "B08". The 20m bands are "B05", "B06", "B07", "B8A", "B11", and "B12". Bands "B01" and "B09" are available at 60m resolution.

For DEAFRICA, sits currently works with collections "S2\_L2A" for Sentinel-2 level 2A and "LS8\_SR" for Landsat-8 ARD collection. (open data). These collections are located in Africa (Capetown) for faster access to African users. No payment for access is required.

For USGS, sits currently works with collection "LANDSAT-C2L2-SR", which corresponds to Landsat Collection 2 Level-2 surface reflectance data, covering Landsat-8 dataset. This collection is requester-pays and requires payment for accessing.

All BDC collections are regularized. BDC users need to provide their credentials using environment variables. To create your credentials, please see <[brazil-data-cube.github.io/applications/dc\\_explorer/token-module.html](http://brazil-data-cube.github.io/applications/dc_explorer/token-module.html)>. Accessing data in the BDC is free. After obtaining the BDC access key, please include it as an environment variable, as follows: `Sys.setenv(BDC_ACCESS_KEY = <your_bdc_access_key>)`

## Examples

```
if (sits_run_examples()) {
  # --- Access to the Brazil Data Cube
  # create a raster cube file based on the information in the BDC
  cbers_tile <- sits_cube(
    source = "BDC",
    collection = "CBERS-WFI-16D",
    bands = c("NDVI", "EVI"),
    tiles = "007004",
    start_date = "2018-09-01",
    end_date = "2019-08-28"
  )
  # --- Access to Digital Earth Africa
  # create a raster cube file based on the information about the files
  # DEAFRICA does not support definition of tiles
  cube_dea <- sits_cube(
    source = "DEAFRICA",
    collection = "SENTINEL-2-L2A",
    bands = c("B04", "B08"),
    roi = c(
      "lat_min" = 17.379,
      "lon_min" = 1.1573,
      "lat_max" = 17.410,
      "lon_max" = 1.1910
    )
  )
}
```

```

    ),
    start_date = "2019-01-01",
    end_date = "2019-10-28"
  )
# --- Access to CDSE open data Sentinel 2/2A level 2 collection
# It is recommended that `multicores` be used to accelerate the process.
s2_cube <- sits_cube(
  source = "CDSE",
  collection = "SENTINEL-2-L2A",
  tiles = c("20LKP"),
  bands = c("B04", "B08", "B11"),
  start_date = "2018-07-18",
  end_date = "2019-01-23"
)

## -- Sentinel-1 SAR from CDSE
roi_sar <- c("lon_min" = 33.546, "lon_max" = 34.999,
            "lat_min" = 1.427, "lat_max" = 3.726)
s1_cube_open <- sits_cube(
  source = "CDSE",
  collection = "SENTINEL-1-RTC",
  bands = c("VV", "VH"),
  orbit = "descending",
  roi = roi_sar,
  start_date = "2020-01-01",
  end_date = "2020-06-10"
)

# --- Access to AWS open data Sentinel 2/2A level 2 collection
s2_cube <- sits_cube(
  source = "AWS",
  collection = "SENTINEL-S2-L2A-COGS",
  tiles = c("20LKP", "20LLP"),
  bands = c("B04", "B08", "B11"),
  start_date = "2018-07-18",
  end_date = "2019-07-23"
)

# -- Creating Sentinel cube from MPC
s2_cube <- sits_cube(
  source = "MPC",
  collection = "SENTINEL-2-L2A",
  tiles = "20LKP",
  bands = c("B05", "CLOUD"),
  start_date = "2018-07-18",
  end_date = "2018-08-23"
)

# -- Creating Landsat cube from MPC
roi <- c("lon_min" = -50.410, "lon_max" = -50.379,
        "lat_min" = -10.1910, "lat_max" = -10.1573)
mpc_cube <- sits_cube(
  source = "MPC",

```

```

        collection = "LANDSAT-C2-L2",
        bands = c("BLUE", "RED", "CLOUD"),
        roi = roi,
        start_date = "2005-01-01",
        end_date = "2006-10-28"
    )

    ## Sentinel-1 SAR from MPC
    roi_sar <- c("lon_min" = -50.410, "lon_max" = -50.379,
               "lat_min" = -10.1910, "lat_max" = -10.1573)

    s1_cube_open <- sits_cube(
        source = "MPC",
        collection = "SENTINEL-1-GRD",
        bands = c("VV", "VH"),
        orbit = "descending",
        roi = roi_sar,
        start_date = "2020-06-01",
        end_date = "2020-09-28"
    )

    # --- Create a cube based on a local MODIS data
    data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
    modis_cube <- sits_cube(
        source = "BDC",
        collection = "MOD13Q1-6",
        data_dir = data_dir
    )
}

```

---

sits\_cube\_copy

*Copy the images of a cube to a local directory*


---

## Description

This function downloads the images of a cube in parallel. A region of interest (*roi*) can be provided to crop the images and a resolution (*res*) to resample the bands.

## Usage

```

sits_cube_copy(
  cube,
  ...,
  roi = NULL,
  res = NULL,
  n_tries = 3,
  multicores = 2L,
  output_dir,
  progress = TRUE
)

```

**Arguments**

cube	A data cube (class "raster_cube")
...	Additional parameters to httr package.
roi	Region of interest. Either an sf_object, a shapefile, or a bounding box vector with named XY values ("xmin", "xmax", "ymin", "ymax") or named lat/long values ("lon_min", "lat_min", "lon_max", "lat_max").
res	An integer value corresponds to the output spatial resolution of the images. Default is NULL.
n_tries	Number of tries to download the same image. Default is 3.
multicores	Number of cores for parallel downloading (integer, min = 1, max = 2048).
output_dir	Output directory where images will be saved. (character vector of length 1).
progress	Logical: show progress bar?

**Value**

Copy of input data cube (class "raster cube").

**Examples**

```
if (sits_run_examples()) {
  # Creating a sits cube from BDC
  bdc_cube <- sits_cube(
    source = "BDC",
    collection = "CBERS-WFI-16D",
    tiles = c("007004", "007005"),
    bands = c("B15", "CLOUD"),
    start_date = "2018-01-01",
    end_date = "2018-01-12"
  )
  # Downloading images to a temporary directory
  cube_local <- sits_cube_copy(
    cube = bdc_cube,
    output_dir = tempdir(),
    roi = c(
      lon_min = -46.5,
      lat_min = -45.5,
      lon_max = -15.5,
      lat_max = -14.6
    ),
    multicores = 2L,
    res = 250,
  )
}
```

---

sits\_factory\_function *Create a closure for calling functions with and without data*

---

## Description

This function implements the factory method pattern. It creates a generic interface to closures in R so that the functions in the sits package can be called in two different ways: 1. Called directly, passing input data and parameters. 2. Called as second-order values (parameters of another function). In the second case, the call will pass no data values and only pass the parameters for execution.

The factory pattern is used in many situations in the sits package, to allow different alternatives for filtering, pattern creation, training, and cross-validation.

Please see the chapter "Technical Annex" in the sits book for details.

## Usage

```
sits_factory_function(data, fun)
```

## Arguments

data	Input data.
fun	Function that performs calculation on the input data.

## Value

A closure that encapsulates the function applied to data.

## Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```
# example code
if (sits_run_examples()) {
  # Include a new machine learning function (multiple linear regression)
  # function that returns mlr model based on a sits sample tibble

  sits_mlr <- function(samples = NULL, formula = sits_formula_linear(),
                       n_weights = 20000, maxit = 2000) {
    train_fun <- function(samples) {
      # Data normalization
      ml_stats <- sits_stats(samples)
      train_samples <- sits_predictors(samples)
      train_samples <- sits_pred_normalize(
        pred = train_samples,
        stats = ml_stats
      )
    }
  }
}
```

```

)
formula <- formula(train_samples[, -1])
# call method and return the trained model
result_mlr <- nnet::multinom(
  formula = formula,
  data = train_samples,
  maxit = maxit,
  MaxNWts = n_weights,
  trace = FALSE,
  na.action = stats::na.fail
)

# construct model predict closure function and returns
predict_fun <- function(values) {
  # retrieve the prediction (values and probs)
  prediction <- tibble::as_tibble(
    stats::predict(result_mlr,
      newdata = values,
      type = "probs"
    )
  )
  return(prediction)
}
class(predict_fun) <- c("sits_model", class(predict_fun))
return(predict_fun)
}
result <- sits_factory_function(samples, train_fun)
return(result)
}
# create an mlr model using a set of samples
mlr_model <- sits_train(samples_modis_ndvi, sits_mlr)
# classify a point
point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
point_class <- sits_classify(point_ndvi, mlr_model, multicores = 1)
plot(point_class)
}

```

---

sits\_filter

*Filter time series with smoothing filter*


---

### Description

Applies a filter to all bands, using a filter function such as `sits_whittaker()` or `sits_sgolay()`.

### Usage

```
sits_filter(data, filter = sits_whittaker())
```

**Arguments**

data            Time series (tibble of class "sits") or matrix.  
 filter         Filter function to be applied.

**Value**

Filtered time series

**Examples**

```
if (sits_run_examples()) {
  # Retrieve a time series with values of NDVI
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  # Filter the point using the Whittaker smoother
  point_whit <- sits_filter(point_ndvi, sits_whittaker(lambda = 3.0))
  # Merge time series
  point_ndvi <- sits_merge(point_ndvi, point_whit,
                          suffix = c("", ".WHIT"))
  # Plot the two points to see the smoothing effect
  plot(point_ndvi)
}
```

---

sits\_formula\_linear    *Define a linear formula for classification models*

---

**Description**

Provides a symbolic description of a fitting model. Tells the model to do a linear transformation of the input values. The 'predictors\_index' parameter informs the positions of fields corresponding to formula independent variables. If no value is given, that all fields will be used as predictors.

**Usage**

```
sits_formula_linear(predictors_index = -2:0)
```

**Arguments**

predictors\_index  
 Index of the valid columns whose names are used to compose formula (default: -2:0).

**Value**

A function that computes a valid formula using a linear function.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Alexandre Ywata de Carvalho, <alexandre.ywata@ipea.gov.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # Example of training a model for time series classification
  # Retrieve the samples for Mato Grosso
  # train an SVM model
  ml_model <- sits_train(samples_modis_ndvi,
    ml_method = sits_svm(formula = sits_formula_logref())
  )
  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  # classify the point
  point_class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
  plot(point_class)
}
```

---

sits\_formula\_logref    *Define a loglinear formula for classification models*

---

**Description**

A function to be used as a symbolic description of some fitting models such as svm and random forest. This function tells the models to do a log transformation of the inputs. The 'predictors\_index' parameter informs the positions of 'tb' fields corresponding to formula independent variables. If no value is given, the default is NULL, a value indicating that all fields will be used as predictors.

**Usage**

```
sits_formula_logref(predictors_index = -2:0)
```

**Arguments**

predictors\_index

Index of the valid columns to compose formula (default: -2:0).

**Value**

A function that computes a valid formula using a log function.



**Author(s)**

Alexandre Ywata de Carvalho, <alexandre.ywata@ipea.gov.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # Example of training a model for time series classification
  # Retrieve the samples for Mato Grosso
  # train an SVM model
  ml_model <- sits_train(samples_modis_ndvi,
    ml_method = sits_svm(formula = sits_formula_logref())
  )
  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  # classify the point
  point_class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
  plot(point_class)
}
```

---

sits_geo_dist	<i>Compute the minimum distances among samples and prediction points.</i>
---------------	---

---

**Description**

Compute the minimum distances among samples and samples to prediction points, following the approach proposed by Meyer and Pebesma(2022).

**Usage**

```
sits_geo_dist(samples, roi, n = 1000L, crs = "EPSG:4326")
```

**Arguments**

samples	Time series (tibble of class "sits").
roi	A region of interest (ROI), either a file containing a shapefile or an "sf" object
n	Maximum number of samples to consider (integer)
crs	CRS of the samples.

**Value**

A tibble with sample-to-sample and sample-to-prediction distances (object of class "distances").

**Author(s)**

Alber Sanchez, <alber.ipia@inpe.br>  
Rolf Simoes, <rolf.simoes@inpe.br>  
Felipe Carvalho, <felipe.carvalho@inpe.br>  
Gilberto Camara, <gilberto.camara@inpe.br>

**References**

Meyer, H., Pebesma, E. "Machine learning-based global maps of ecological variables and the challenge of assessing them", Nature Communications 13, 2208 (2022). <https://doi.org/10.1038/s41467-022-29838-9>

**Examples**

```
if (sits_run_examples()) {  
  # read a shapefile for the state of Mato Grosso, Brazil  
  mt_shp <- system.file("extdata/shapefiles/mato_grosso/mt.shp",  
    package = "sits"  
  )  
  # convert to an sf object  
  mt_sf <- sf::read_sf(mt_shp)  
  # calculate sample-to-sample and sample-to-prediction distances  
  distances <- sits_geo_dist(  
    samples = samples_modis_ndvi,  
    roi = mt_sf  
  )  
  # plot sample-to-sample and sample-to-prediction distances  
  plot(distances)  
}
```

---

sits\_get\_data

*Get time series from data cubes and cloud services*

---

**Description**

Retrieve a set of time series from a data cube or from a time series service. Data cubes and puts it in a "sits tibble". Sits tibbles are the main structures of sits package. They contain both the satellite image time series and their metadata.

**Usage**

```
sits_get_data(  
  cube,  
  samples,  
  ...,  
  start_date = NULL,  
  end_date = NULL,
```

```
    label = "NoClass",
    bands = sits_bands(cube),
    crs = "EPSG:4326",
    impute_fn = impute_linear(),
    label_attr = NULL,
    n_sam_pol = 30L,
    pol_avg = FALSE,
    pol_id = NULL,
    sampling_type = "random",
    multicores = 2L,
    progress = TRUE
)

## Default S3 method:
sits_get_data(cube, samples, ...)

## S3 method for class 'csv'
sits_get_data(
  cube,
  samples,
  ...,
  bands = sits_bands(cube),
  crs = "EPSG:4326",
  impute_fn = impute_linear(),
  multicores = 2,
  progress = FALSE
)

## S3 method for class 'shp'
sits_get_data(
  cube,
  samples,
  ...,
  label = "NoClass",
  start_date = NULL,
  end_date = NULL,
  bands = sits_bands(cube),
  impute_fn = impute_linear(),
  label_attr = NULL,
  n_sam_pol = 30,
  pol_avg = FALSE,
  pol_id = NULL,
  sampling_type = "random",
  multicores = 2,
  progress = FALSE
)

## S3 method for class 'sf'
```

```

sits_get_data(
  cube,
  samples,
  ...,
  start_date = NULL,
  end_date = NULL,
  bands = sits_bands(cube),
  impute_fn = impute_linear(),
  label = "NoClass",
  label_attr = NULL,
  n_sam_pol = 30,
  pol_avg = FALSE,
  pol_id = NULL,
  sampling_type = "random",
  multicores = 2,
  progress = FALSE
)

## S3 method for class 'sits'
sits_get_data(
  cube,
  samples,
  ...,
  bands = sits_bands(cube),
  impute_fn = impute_linear(),
  multicores = 2,
  progress = FALSE
)

## S3 method for class 'data.frame'
sits_get_data(
  cube,
  samples,
  ...,
  start_date = NULL,
  end_date = NULL,
  bands = sits_bands(cube),
  label = "NoClass",
  crs = "EPSG:4326",
  impute_fn = impute_linear(),
  multicores = 2,
  progress = FALSE
)

```

### Arguments

cube	Data cube from where data is to be retrieved. (tibble of class "raster_cube").
samples	Location of the samples to be retrieved. Either a tibble of class "sits", an "sf" ob-

	ject, the name of a shapefile or csv file, or a data.frame with columns "longitude" and "latitude".
...	Specific parameters for specific cases.
start_date	Start of the interval for the time series - optional (Date in "YYYY-MM-DD" format).
end_date	End of the interval for the time series - optional (Date in "YYYY-MM-DD" format).
label	Label to be assigned to the time series (optional) (character vector of length 1).
bands	Bands to be retrieved - optional (character vector).
crs	Default crs for the samples (character vector of length 1).
impute_fn	Imputation function to remove NA.
label_attr	Attribute in the shapefile or sf object to be used as a polygon label. (character vector of length 1).
n_sam_pol	Number of samples per polygon to be read for POLYGON or MULTIPOLYGON shapefiles or sf objects (single integer).
pol_avg	Logical: summarize samples for each polygon?
pol_id	ID attribute for polygons (character vector of length 1)
sampling_type	Spatial sampling type: random, hexagonal, regular, or Fibonacci.
multicores	Number of threads to process the time series (integer, with min = 1 and max = 2048).
progress	Logical: show progress bar?

**Value**

A tibble of class "sits" with set of time series <longitude, latitude, start\_date, end\_date, label, cube, time\_series>.

**Note**

There are four ways of specifying data to be retrieved using the `samples` parameter: (a) CSV file: a CSV file with columns `longitude`, `latitude`, `start_date`, `end_date` and `label` for each sample; (b) SHP file: a shapefile in POINT or POLYGON geometry containing the location of the samples and an attribute to be used as label. Also, provide start and end date for the time series; (c) sits object: A sits tibble; (d) sf object: An `link[sf]{sf}` object with POINT or POLYGON geometry; (e) data.frame: A data.frame with with mandatory columns `longitude` and `latitude`.

**Author(s)**

Gilberto Camara

**Examples**

```

if (sits_run_examples()) {
  # reading a lat/long from a local cube
  # create a cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  raster_cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  samples <- tibble::tibble(longitude = -55.66738, latitude = -11.76990)
  point_ndvi <- sits_get_data(raster_cube, samples)
  #
  # reading samples from a cube based on a CSV file
  csv_file <- system.file("extdata/samples/samples_sinop_crop.csv",
    package = "sits"
  )
  points <- sits_get_data(cube = raster_cube, samples = csv_file)

  # reading a shapefile from BDC (Brazil Data Cube)
  bdc_cube <- sits_cube(
    source = "BDC",
    collection = "CBERS-WFI-16D",
    bands = c("NDVI", "EVI"),
    tiles = c("007004", "007005"),
    start_date = "2018-09-01",
    end_date = "2018-10-28"
  )
  # define a shapefile to be read from the cube
  shp_file <- system.file("extdata/shapefiles/bdc-test/samples.shp",
    package = "sits"
  )
  # get samples from the BDC based on the shapefile
  time_series_bdc <- sits_get_data(
    cube = bdc_cube,
    samples = shp_file
  )
}

```

---

sits\_impute

*Replace NA values in time series with imputation function*


---

**Description**

Remove NA

**Usage**

```
sits_impute(samples, impute_fn = impute_linear())
```

**Arguments**

samples	A time series tibble
impute_fn	Imputation function

**Value**

A set of filtered time series using the imputation function.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

---

sits\_kfold\_validate    *Cross-validate time series samples*

---

**Description**

Splits the set of time series into training and validation and perform k-fold cross-validation. Cross-validation is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform. One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set).

The k-fold cross validation method involves splitting the dataset into k-subsets. For each subset is held out while the model is trained on all other subsets. This process is completed until accuracy is determine for each instance in the dataset, and an overall accuracy estimate is provided.

This function returns the confusion matrix, and Kappa values.

**Usage**

```
sits_kfold_validate(  
  samples,  
  folds = 5,  
  ml_method = sits_rfor(),  
  multicores = 2  
)
```

**Arguments**

samples	Time series.
folds	Number of partitions to create.
ml_method	Machine learning method.
multicores	Number of cores to process in parallel.

**Value**

A `caret::confusionMatrix` object to be used for validation assessment.

**Note**

Please refer to the sits documentation available in [<https://e-sensing.github.io/sitsbook/>](https://e-sensing.github.io/sitsbook/) for detailed examples.

**Author(s)**

Rolf Simoes, [<rolf.simoes@inpe.br>](mailto:rolf.simoes@inpe.br)

Gilberto Camara, [<gilberto.camara@inpe.br>](mailto:gilberto.camara@inpe.br)

**Examples**

```
if (sits_run_examples()) {
  # A dataset containing a tibble with time series samples
  # for the Mato Grosso state in Brasil
  # create a list to store the results
  results <- list()
  # accuracy assessment lightTAE
  acc_rfor <- sits_kfold_validate(
    samples_modis_ndvi,
    folds = 5,
    ml_method = sits_rfor()
  )
  # use a name
  acc_rfor$name <- "Rfor"
  # put the result in a list
  results[[length(results) + 1]] <- acc_rfor
  # save to xlsx file
  sits_to_xlsx(
    results,
    file = tempfile("accuracy_mato_grosso_dl_", fileext = ".xlsx")
  )
}
```

---

sits\_labels

*Get labels associated to a data set*

---

**Description**

Finds labels in a sits tibble or data cube



**Usage**

```
sits_labels(data)

## S3 method for class 'sits'
sits_labels(data)

## S3 method for class 'derived_cube'
sits_labels(data)

## S3 method for class 'derived_vector_cube'
sits_labels(data)

## S3 method for class 'raster_cube'
sits_labels(data)

## S3 method for class 'patterns'
sits_labels(data)

## S3 method for class 'sits_model'
sits_labels(data)

## Default S3 method:
sits_labels(data)
```

**Arguments**

`data` Time series (tibble of class "sits"), patterns (tibble of class "patterns"), data cube (tibble of class "raster\_cube"), or model (closure of class "sits\_model").

**Value**

The labels of the input data (character vector).

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # get the labels for a time series set
  labels_ts <- sits_labels(samples_modis_ndvi)
  # get labels for a set of patterns
  labels_pat <- sits_labels(sits_patterns(samples_modis_ndvi))
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # get labels for the model
  labels_mod <- sits_labels(rfor_model)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
}
```

```
cube <- sits_cube(  
  source = "BDC",  
  collection = "MOD13Q1-6",  
  data_dir = data_dir  
)  
# classify a data cube  
probs_cube <- sits_classify(  
  data = cube, ml_model = rfor_model, output_dir = tempdir()  
)  
# get the labels for a probs cube  
labels_probs <- sits_labels(probs_cube)  
}
```

---

sits\_labels\_summary    *Inform label distribution of a set of time series*

---

## Description

Describes labels in a sits tibble

## Usage

```
sits_labels_summary(data)  
  
## S3 method for class 'sits'  
sits_labels_summary(data)
```

## Arguments

data                    Data.frame - Valid sits tibble

## Value

A tibble with the frequency of each label.

## Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

## Examples

```
# read a tibble with 400 samples of Cerrado and 346 samples of Pasture  
data(cerrado_2classes)  
# print the labels  
sits_labels_summary(cerrado_2classes)
```

---

`sits_label_classification`*Build a labelled image from a probability cube*

---

**Description**

Takes a set of classified raster layers with probabilities, and label them based on the maximum probability for each pixel.

**Usage**

```
sits_label_classification(  
  cube,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1",  
  progress = TRUE  
)  
  
## S3 method for class 'probs_cube'  
sits_label_classification(  
  cube,  
  ...,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1",  
  progress = TRUE  
)  
  
## S3 method for class 'probs_vector_cube'  
sits_label_classification(  
  cube,  
  ...,  
  output_dir,  
  version = "v1",  
  progress = TRUE  
)  
  
## S3 method for class 'raster_cube'  
sits_label_classification(cube, ...)  
  
## S3 method for class 'derived_cube'  
sits_label_classification(cube, ...)  
  
## Default S3 method:
```

```
sits_label_classification(cube, ...)
```

### Arguments

cube	Classified image data cube.
memsize	maximum overall memory (in GB) to label the classification.
multicores	Number of workers to label the classification in parallel.
output_dir	Output directory for classified files.
version	Version of resulting image (in the case of multiple runs).
progress	Show progress bar?
...	Other parameters for specific functions.

### Value

A data cube with an image with the classified map.

### Note

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>  
 Felipe Souza, <felipe.souza@inpe.br>

### Examples

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # plot the probability cube
  plot(probs_cube)
  # smooth the probability cube using Bayesian statistics
  bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
  # plot the smoothed cube
  plot(bayes_cube)
  # label the probability cube
```

```

    label_cube <- sits_label_classification(
      bayes_cube,
      output_dir = tempdir()
    )
    # plot the labelled cube
    plot(label_cube)
  }

```

---

sits\_lighttae

*Train a model using Lightweight Temporal Self-Attention Encoder*


---

### Description

Implementation of Light Temporal Attention Encoder (L-TAE) for satellite image time series

This function is based on the paper by Vivien Garnot referenced below and code available on github at <https://github.com/VSainteuf/lightweight-temporal-attention-pytorch> If you use this method, please cite the original TAE and the LTAE paper.

We also used the code made available by Maja Schneider in her work with Marco Körner referenced below and available at <https://github.com/maja601/RC2020-psetae>.

### Usage

```

sits_lighttae(
  samples = NULL,
  samples_validation = NULL,
  epochs = 150L,
  batch_size = 128L,
  validation_split = 0.2,
  optimizer = torch::optim_adamw,
  opt_hparams = list(lr = 0.005, eps = 1e-08, weight_decay = 1e-06),
  lr_decay_epochs = 50L,
  lr_decay_rate = 1,
  patience = 20L,
  min_delta = 0.01,
  verbose = FALSE
)

```

### Arguments

<code>samples</code>	Time series with the training samples (tibble of class "sits").
<code>samples_validation</code>	Time series with the validation samples (tibble of class "sits"). If <code>samples_validation</code> parameter is provided, <code>validation_split</code> is ignored.
<code>epochs</code>	Number of iterations to train the model (integer, min = 1, max = 20000).
<code>batch_size</code>	Number of samples per gradient update (integer, min = 16L, max = 2048L)

validation_split	Fraction of training data to be used as validation data.
optimizer	Optimizer function to be used.
opt_hparams	Hyperparameters for optimizer: lr : Learning rate of the optimizer eps: Term added to the denominator to improve numerical stability. weight_decay: L2 regularization rate.
lr_decay_epochs	Number of epochs to reduce learning rate.
lr_decay_rate	Decay factor for reducing learning rate.
patience	Number of epochs without improvements until training stops.
min_delta	Minimum improvement in loss function to reset the patience counter.
verbose	Verbosity mode (TRUE/FALSE). Default is FALSE.

**Value**

A fitted model to be used for classification of data cubes.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Charlotte Pelletier, <charlotte.pelletier@univ-ubs.fr>

**References**

Vivien Garnot, Loic Landrieu, Sebastien Giordano, and Nesrine Chehata, "Satellite Image Time Series Classification with Pixel-Set Encoders and Temporal Self-Attention", 2020 Conference on Computer Vision and Pattern Recognition. pages 12322-12331. DOI: 10.1109/CVPR42600.2020.01234

Vivien Garnot, Loic Landrieu, "Lightweight Temporal Self-Attention for Classifying Satellite Images Time Series", arXiv preprint arXiv:2007.00586, 2020.

Schneider, Maja; Körner, Marco, "[Re] Satellite Image Time Series Classification with Pixel-Set Encoders and Temporal Self-Attention." ReScience C 7 (2), 2021. DOI: 10.5281/zenodo.4835356

**Examples**

```
if (sits_run_examples()) {
  # create a lightTAE model
  torch_model <- sits_train(samples_modis_ndvi, sits_lighttAE())
  # plot the model
  plot(torch_model)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
}
```

```
# classify a data cube
probs_cube <- sits_classify(
  data = cube, ml_model = torch_model, output_dir = tempdir()
)
# plot the probability cube
plot(probs_cube)
# smooth the probability cube using Bayesian statistics
bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
# plot the smoothed cube
plot(bayes_cube)
# label the probability cube
label_cube <- sits_label_classification(
  bayes_cube,
  output_dir = tempdir()
)
# plot the labelled cube
plot(label_cube)
}
```

---

sits\_list\_collections *List the cloud collections supported by sits*

---

### Description

Prints the collections available in each cloud service supported by sits. Users can select to get information only for a single service by using the source parameter.

### Usage

```
sits_list_collections(source = NULL)
```

### Arguments

source            Data source to be shown in detail.

### Value

Prints collections available in each cloud service supported by sits.

### Examples

```
if (sits_run_examples()) {
  # show the names of the colors supported by SITS
  sits_list_collections()
}
```

---

`sits_merge`*Merge two data sets (time series or cubes)*

---

## Description

To merge two series, we consider that they contain different attributes but refer to the same data cube, and spatiotemporal location. This function is useful to merge different bands of the same locations. For example, one may want to put the raw and smoothed bands for the same set of locations in the same tibble.

To merge data cubes, they should share the same sensor, resolution, bounding box, timeline, and have different bands.

## Usage

```
sits_merge(data1, data2, ...)

## S3 method for class 'sits'
sits_merge(data1, data2, ..., suffix = c(".1", ".2"))

## S3 method for class 'sar_cube'
sits_merge(data1, data2, ...)

## S3 method for class 'raster_cube'
sits_merge(data1, data2, ...)

## Default S3 method:
sits_merge(data1, data2, ...)
```

## Arguments

<code>data1</code>	Time series (tibble of class "sits") or data cube (tibble of class "raster_cube").
<code>data2</code>	Time series (tibble of class "sits") or data cube (tibble of class "raster_cube").
<code>...</code>	Additional parameters
<code>suffix</code>	If there are duplicate bands in <code>data1</code> and <code>data2</code> these suffixes will be added (character vector).

## Value

merged data sets (tibble of class "sits" or tibble of class "raster\_cube")

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>



**Examples**

```
if (sits_run_examples()) {  
  # Retrieve a time series with values of NDVI  
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")  
  
  # Filter the point using the Whittaker smoother  
  point_whit <- sits_filter(point_ndvi, sits_whittaker(lambda = 3.0))  
  # Merge time series  
  point_ndvi <- sits_merge(point_ndvi, point_whit, suffix = c("", ".WHIT"))  
  
  # Plot the two points to see the smoothing effect  
  plot(point_ndvi)  
}
```

---

sits_mgrs_to_roi	<i>Convert MGRS tile information to ROI in WGS84</i>
------------------	--

---

**Description**

Takes a list of MGRS tiles and produces a ROI covering them

**Usage**

```
sits_mgrs_to_roi(tiles)
```

**Arguments**

tiles            Character vector with names of MGRS tiles

**Value**

roi Valid ROI to use in other SITS functions

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@gmail.com>

---

sits\_mixture\_model      *Multiple endmember spectral mixture analysis*

---

### Description

Create a multiple endmember spectral mixture analyses fractions images. We use the non-negative least squares (NNLS) solver to calculate the fractions of each endmember. The NNLS was implemented by Jakob Schwalb-Willmann in RStoolbox package (licensed as GPL>=3).

### Usage

```
sits_mixture_model(  
  data,  
  endmembers,  
  ...,  
  rmse_band = TRUE,  
  multicores = 2,  
  progress = TRUE  
)  
  
## S3 method for class 'sits'  
sits_mixture_model(  
  data,  
  endmembers,  
  ...,  
  rmse_band = TRUE,  
  multicores = 2,  
  progress = TRUE  
)  
  
## S3 method for class 'raster_cube'  
sits_mixture_model(  
  data,  
  endmembers,  
  ...,  
  rmse_band = TRUE,  
  memsize = 4,  
  multicores = 2,  
  output_dir,  
  progress = TRUE  
)  
  
## S3 method for class 'derived_cube'  
sits_mixture_model(data, endmembers, ...)  
  
## S3 method for class 'tbl_df'  
sits_mixture_model(data, endmembers, ...)
```

```
## Default S3 method:  
sits_mixture_model(data, endmembers, ...)
```

### Arguments

data	A sits data cube or a sits tibble.
endmembers	Reference spectral endmembers. (see details below).
...	Parameters for specific functions.
rmse_band	A boolean indicating whether the error associated with the linear model should be generated. If true, a new band with errors for each pixel is generated using the root mean square measure (RMSE). Default is TRUE.
multicores	Number of cores to be used for generate the mixture model.
progress	Show progress bar? Default is TRUE.
memsizes	Memory available for the mixture model (in GB).
output_dir	Directory for output images.

### Details

The endmembers parameter should be a tibble, csv or a shapefile. endmembers parameter must have the following columns: type, which defines the endmembers that will be created and the columns corresponding to the bands that will be used in the mixture model. The band values must follow the product scale. For example, in the case of sentinel-2 images the bands should be in the range 0 to 1. See the example in this documentation for more details.

### Value

In case of a cube, a sits cube with the fractions of each endmember will be returned. The sum of all fractions is restricted to 1 (scaled from 0 to 10000), corresponding to the abundance of the endmembers in the pixels. In case of a tibble sits, the time series will be returned with the values corresponding to each fraction.

### Author(s)

Felipe Carvalho, <felipe.carvalho@inpe.br>  
Felipe Carlos, <efelipecarlos@gmail.com>  
Rolf Simoes, <rolf.simoes@inpe.br>  
Gilberto Camara, <gilberto.camara@inpe.br>  
Alber Sanchez, <alber.ipia@inpe.br>

### References

RStoolbox package (<https://github.com/bleutner/RStoolbox/>)

**Examples**

```

if (sits_run_examples()) {
  # Create a sentinel-2 cube
  s2_cube <- sits_cube(
    source = "AWS",
    collection = "SENTINEL-2-L2A",
    tiles = "20LKP",
    bands = c("B02", "B03", "B04", "B8A", "B11", "B12", "CLOUD"),
    start_date = "2019-06-13",
    end_date = "2019-06-30"
  )
  # create a directory to store the regularized file
  reg_dir <- paste0(tempdir(), "/mix_model")
  dir.create(reg_dir)
  # Cube regularization for 16 days and 160 meters
  reg_cube <- sits_regularize(
    cube = s2_cube,
    period = "P16D",
    res = 160,
    roi = c(
      lon_min = -65.54870165,
      lat_min = -10.63479162,
      lon_max = -65.07629670,
      lat_max = -10.36046639
    ),
    multicores = 2,
    output_dir = reg_dir
  )

  # Create the endmembers tibble
  em <- tibble::tribble(
    ~class, ~B02, ~B03, ~B04, ~B8A, ~B11, ~B12,
    "forest", 0.02, 0.0352, 0.0189, 0.28, 0.134, 0.0546,
    "land", 0.04, 0.065, 0.07, 0.36, 0.35, 0.18,
    "water", 0.07, 0.11, 0.14, 0.085, 0.004, 0.0026
  )

  # Generate the mixture model
  mm <- sits_mixture_model(
    data = reg_cube,
    endmembers = em,
    memsize = 4,
    multicores = 2,
    output_dir = tempdir()
  )
}

```

**Description**

Use a multi-layer perceptron algorithm to classify data. This function uses the R "torch" and "luz" packages. Please refer to the documentation of those package for more details.

**Usage**

```
sits_mlp(
  samples = NULL,
  samples_validation = NULL,
  layers = c(512, 512, 512),
  dropout_rates = c(0.2, 0.3, 0.4),
  optimizer = torchopt::optim_adamw,
  opt_hparams = list(lr = 0.001, eps = 1e-08, weight_decay = 1e-06),
  epochs = 100,
  batch_size = 64,
  validation_split = 0.2,
  patience = 20,
  min_delta = 0.01,
  verbose = FALSE
)
```

**Arguments**

<code>samples</code>	Time series with the training samples.
<code>samples_validation</code>	Time series with the validation samples. if the <code>samples_validation</code> parameter is provided, the <code>validation_split</code> parameter is ignored.
<code>layers</code>	Vector with number of hidden nodes in each layer.
<code>dropout_rates</code>	Vector with the dropout rates (0,1) for each layer.
<code>optimizer</code>	Optimizer function to be used.
<code>opt_hparams</code>	Hyperparameters for optimizer: <code>lr</code> : Learning rate of the optimizer <code>eps</code> : Term added to the denominator to improve numerical stability.. <code>weight_decay</code> : L2 regularization
<code>epochs</code>	Number of iterations to train the model.
<code>batch_size</code>	Number of samples per gradient update.
<code>validation_split</code>	Number between 0 and 1. Fraction of the training data for validation. The model will set apart this fraction and will evaluate the loss and any model metrics on this data at the end of each epoch.
<code>patience</code>	Number of epochs without improvements until training stops.
<code>min_delta</code>	Minimum improvement in loss function to reset the patience counter.
<code>verbose</code>	Verbosity mode (TRUE/FALSE). Default is FALSE.

**Value**

A torch mlp model to be used for classification.

**Note**

The default parameters for the MLP have been chosen based on the work by Wang et al. 2017 that takes multilayer perceptrons as the baseline for time series classifications: (a) Three layers with 512 neurons each, specified by the parameter 'layers'; (b) dropout rates of 10 (c) the "optimizer\_adam" as optimizer (default value); (d) a number of training steps ('epochs') of 100; (e) a 'batch\_size' of 64, which indicates how many time series are used for input at a given steps; (f) a validation percentage of 20 will be randomly set side for validation. (g) The "relu" activation function.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**References**

Zhiguang Wang, Weizhong Yan, and Tim Oates, "Time series classification from scratch with deep neural networks: A strong baseline", 2017 international joint conference on neural networks (IJCNN).

**Examples**

```
if (sits_run_examples()) {
  # create an MLP model
  torch_model <- sits_train(samples_modis_ndvi, sits_mlp())
  # plot the model
  plot(torch_model)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = torch_model, output_dir = tempdir()
  )
  # plot the probability cube
  plot(probs_cube)
  # smooth the probability cube using Bayesian statistics
  bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
  # plot the smoothed cube
  plot(bayes_cube)
  # label the probability cube
  label_cube <- sits_label_classification(
    bayes_cube,
    output_dir = tempdir()
  )
  # plot the labelled cube
  plot(label_cube)
}
```

---

sits\_model\_export      *Export classification models*

---

**Description**

Given a trained machine learning or deep learning model, exports the model as an object for further exploration outside the sits package.

**Usage**

```
sits_model_export(ml_model)

## S3 method for class 'sits_model'
sits_model_export(ml_model)
```

**Arguments**

ml\_model      A trained machine learning model

**Value**

An R object containing the model in the original format of machine learning or deep learning package.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a classification model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # export the model
  rfor_object <- sits_model_export(rfor_model)
}
```

---

sits\_mosaic      *Mosaic classified cubes*

---

**Description**

Creates a mosaic of all tiles of a sits cube. Mosaics can be created from EO cubes and derived cubes. In sits EO cubes, the mosaic will be generated for each band and date. It is recommended to filter the image with the less cloud cover to create a mosaic for the EO cubes. It is possible to provide a roi to crop the mosaic.

**Usage**

```
sits_mosaic(
  cube,
  crs = "EPSG:3857",
  roi = NULL,
  multicores = 2,
  output_dir,
  version = "v1",
  progress = TRUE
)
```

**Arguments**

cube	A sits data cube.
crs	A target coordinate reference system of raster mosaic. The provided crs could be a string (e.g. "EPSG:4326" or a proj4string), or an EPSG code number (e.g. 4326). Default is "EPSG:3857" - WGS 84 / Pseudo-Mercator.
roi	Region of interest (see below).
multicores	Number of cores that will be used to crop the images in parallel.
output_dir	Directory for output images.
version	Version of resulting image (in the case of multiple tests)
progress	Show progress bar? Default is TRUE.

**Value**

a sits cube with only one tile.

**Note**

The "roi" parameter defines a region of interest. It can be an `sf_object`, a shapefile, or a bounding box vector with named XY values (`xmin`, `xmax`, `ymin`, `ymax`) or named lat/long values (`lon_min`, `lon_max`, `lat_min`, `lat_max`).

The user should specify the crs of the mosaic since in many cases the input images will be in different coordinate systems. For example, when mosaicking Sentinel-2 images the inputs will be in general in different UTM grid zones.

**Author(s)**

Felipe Carvalho, <felipe.carvalho@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
```



```

data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
cube <- sits_cube(
  source = "BDC",
  collection = "MOD13Q1-6",
  data_dir = data_dir
)
# classify a data cube
probs_cube <- sits_classify(
  data = cube, ml_model = rfor_model, output_dir = tempdir()
)
# smooth the probability cube using Bayesian statistics
bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
# label the probability cube
label_cube <- sits_label_classification(
  bayes_cube,
  output_dir = tempdir()
)
# create roi
roi <- sf::st_sfc(
  sf::st_polygon(
    list(rbind(
      c(-55.64768, -11.68649),
      c(-55.69654, -11.66455),
      c(-55.62973, -11.61519),
      c(-55.64768, -11.68649)
    ))
  ),
  crs = "EPSG:4326"
)
# crop and mosaic classified image
mosaic_cube <- sits_mosaic(
  cube = label_cube,
  roi = roi,
  crs = "EPSG:4326",
  output_dir = tempdir()
)
}

```

---

## Description

This function takes a set of time series samples as input estimates a set of patterns. The patterns are calculated using a GAM model. The idea is to use a formula of type  $y \sim s(x)$ , where  $x$  is a temporal reference and  $y$  if the value of the signal. For each time, there will be as many predictions as there are sample values. The GAM model predicts a suitable approximation that fits the assumptions of the statistical model, based on a smooth function.

This method is based on the "createPatterns" method of the dtwSat package, which is also described in the reference paper.

**Usage**

```
sits_patterns(data = NULL, freq = 8, formula = y ~ s(x), ...)
```

**Arguments**

data	Time series.
freq	Interval in days for estimates.
formula	Formula to be applied in the estimate.
...	Any additional parameters.

**Value**

Time series with patterns.

**Author(s)**

Victor Maus, <vwmaus1@gmail.com>  
Gilberto Camara, <gilberto.camara@inpe.br>  
Rolf Simoes, <rolf.simoes@inpe.br>

**References**

Maus V, Camara G, Cartaxo R, Sanchez A, Ramos F, Queiroz GR. A Time-Weighted Dynamic Time Warping Method for Land-Use and Land-Cover Mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9(8):3729-3739, August 2016. ISSN 1939-1404. doi:10.1109/JSTARS.2016.2517118.

**Examples**

```
if (sits_run_examples()) {  
  patterns <- sits_patterns(cerrado_2classes)  
  plot(patterns)  
}
```

---

sits\_predictors

*Obtain predictors for time series samples*

---

**Description**

Predictors are X-Y values required for machine learning algorithms, organized as a data table where each row corresponds to a training sample. The first two columns of the predictors table are categorical (label\_id and label). The other columns are the values of each band and time, organized first by band and then by time.

**Usage**

```
sits_predictors(samples)
```

**Arguments**

samples            Time series in sits format (tibble of class "sits")

**Value**

The predictors for the sample: a data.frame with one row per sample.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  pred <- sits_predictors(samples_modis_ndvi)  
}
```

---

sits\_pred\_features     *Obtain numerical values of predictors for time series samples*

---

**Description**

Predictors are X-Y values required for machine learning algorithms, organized as a data table where each row corresponds to a training sample. The first two columns of the predictors table are categorical ("label\_id" and "label"). The other columns are the values of each band and time, organized first by band and then by time. This function returns the numeric values associated to each sample.

**Usage**

```
sits_pred_features(pred)
```

**Arguments**

pred                X-Y predictors: a data.frame with one row per sample.

**Value**

The Y predictors for the sample: data.frame with one row per sample.

**Note**

Please refer to the sits documentation available in <<https://e-sensing.github.io/sitsbook/>> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  pred <- sits_predictors(samples_modis_ndvi)  
  features <- sits_pred_features(pred)  
}
```

---

sits\_pred\_normalize    *Normalize predictor values*

---

**Description**

Most machine learning algorithms require data to be normalized. This applies to the "SVM" method and to all deep learning ones. To normalize the predictors, it is required that the statistics per band for each sample have been obtained by the "sits\_stats" function.

**Usage**

```
sits_pred_normalize(pred, stats)
```

**Arguments**

pred	X-Y predictors: a data.frame with one row per sample.
stats	Values of time series for Q02 and Q98 of the data (list of numeric values with two elements)

**Value**

A data.frame with normalized predictor values

**Note**

Please refer to the sits documentation available in <<https://e-sensing.github.io/sitsbook/>> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  stats <- sits_stats(samples_modis_ndvi)  
  pred <- sits_predictors(samples_modis_ndvi)  
  pred_norm <- sits_pred_normalize(pred, stats)  
}
```

---

sits\_pred\_reference     *Obtain categorical id and predictor labels for time series samples*

---

### Description

Predictors are X-Y values required for machine learning algorithms, organized as a data table where each row corresponds to a training sample. The first two columns of the predictors table are categorical ("label\_id" and "label"). The other columns are the values of each band and time, organized first by band and then by time. This function returns the numeric values associated to each sample.

### Usage

```
sits_pred_references(pred)
```

### Arguments

pred                    X-Y predictors: a data.frame with one row per sample.

### Value

A character vector with labels associated to training samples.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

### Examples

```
if (sits_run_examples()) {  
  pred <- sits_predictors(samples_modis_ndvi)  
  ref <- sits_pred_references(pred)  
}
```

---

sits\_pred\_sample             *Obtain a fraction of the predictors data frame*

---

### Description

Many machine learning algorithms (especially deep learning) use part of the original samples as test data to adjust its hyperparameters and to find an optimal point of convergence using gradient descent. This function extracts a fraction of the predictors to serve as test values for the deep learning algorithm.

### Usage

```
sits_pred_sample(pred, frac)
```

**Arguments**

pred            X-Y predictors: a data.frame with one row per sample.  
frac            Fraction of the X-Y predictors to be extracted

**Value**

A data.frame with the chosen fraction of the X-Y predictors.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  pred <- sits_predictors(samples_modis_ndvi)  
  pred_frac <- sits_pred_sample(pred, frac = 0.5)  
}
```

---

sits_reclassify	<i>Reclassify a classified cube</i>
-----------------	-------------------------------------

---

**Description**

Apply a set of named expressions to reclassify a classified image. The expressions should use character values to refer to labels in logical expressions.

**Usage**

```
sits_reclassify(  
  cube,  
  mask,  
  rules,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)  
  
## S3 method for class 'class_cube'  
sits_reclassify(  
  cube,
```

```
    mask,
    rules,
    memsize = 4L,
    multicores = 2L,
    output_dir,
    version = "v1"
)

## Default S3 method:
sits_reclassify(
  cube,
  mask,
  rules,
  memsize,
  multicores,
  output_dir,
  version = "v1"
)
```

### Arguments

cube	Image cube to be reclassified (class = "class_cube")
mask	Image cube with additional information to be used in expressions (class = "class_cube").
rules	Expressions to be evaluated (named list).
memsize	Memory available for classification in GB (integer, min = 1, max = 16384).
multicores	Number of cores to be used for classification (integer, min = 1, max = 2048).
output_dir	Directory where files will be saved (character vector of length 1 with valid location).
version	Version of resulting image (character).

### Details

sits\_reclassify() allow any valid R expression to compute reclassification. User should refer to cube and mask to construct logical expressions. Users can use any R expression that evaluates to logical. TRUE values will be relabeled to expression name. Updates are done in asynchronous manner, that is, all expressions are evaluated using original classified values. Expressions are evaluated sequentially and resulting values are assigned to output cube. Last expressions has precedence over first ones.

### Value

An object of class "class\_cube" (reclassified cube).

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
# Open mask map
data_dir <- system.file("extdata/raster/prodes", package = "sits")
prodes2021 <- sits_cube(
  source = "USGS",
  collection = "LANDSAT-C2L2-SR",
  data_dir = data_dir,
  parse_info = c(
    "X1", "X2", "tile", "start_date", "end_date",
    "band", "version"
  ),
  bands = "class",
  version = "v20220606",
  labels = c("1" = "Forest", "2" = "Water", "3" = "NonForest",
    "4" = "NonForest2", "6" = "d2007", "7" = "d2008",
    "8" = "d2009", "9" = "d2010", "10" = "d2011",
    "11" = "d2012", "12" = "d2013", "13" = "d2014",
    "14" = "d2015", "15" = "d2016", "16" = "d2017",
    "17" = "d2018", "18" = "r2010", "19" = "r2011",
    "20" = "r2012", "21" = "r2013", "22" = "r2014",
    "23" = "r2015", "24" = "r2016", "25" = "r2017",
    "26" = "r2018", "27" = "d2019", "28" = "r2019",
    "29" = "d2020", "31" = "r2020", "32" = "Clouds2021",
    "33" = "d2021", "34" = "r2021"),
  progress = FALSE
)
#' Open classification map
data_dir <- system.file("extdata/raster/classif", package = "sits")
ro_class <- sits_cube(
  source = "MPC",
  collection = "SENTINEL-2-L2A",
  data_dir = data_dir,
  parse_info = c(
    "X1", "X2", "tile", "start_date", "end_date",
    "band", "version"
  ),
  bands = "class",
  labels = c(
    "1" = "ClearCut_Fire", "2" = "ClearCut_Soil",
    "3" = "ClearCut_Veg", "4" = "Forest"
  ),
  progress = FALSE
)
# Reclassify cube
ro_mask <- sits_reclassify(
  cube = ro_class,
  mask = prodes2021,
  rules = list(
    "Old_Deforestation" = mask %in% c(
      "d2007", "d2008", "d2009",
      "d2010", "d2011", "d2012",

```



```

        "d2013", "d2014", "d2015",
        "d2016", "d2017", "d2018",
        "r2010", "r2011", "r2012",
        "r2013", "r2014", "r2015",
        "r2016", "r2017", "r2018",
        "d2019", "r2019", "d2020",
        "r2020", "r2021"
    ),
    "Water_Mask" = mask == "Water",
    "NonForest_Mask" = mask %in% c("NonForest", "NonForest2")
),
memsize = 4,
multicores = 2,
output_dir = tempdir(),
version = "ex_reclassify"
)
}

```

---

sits\_reduce

*Reduces a cube or samples from a summarization function*


---

### Description

Apply a temporal reduction from a named expression in cube or sits tibble. In the case of cubes, it materializes a new band in output\_dir. The result will be a cube with only one date with the raster reduced from the function.

### Usage

```

sits_reduce(data, ...)

## S3 method for class 'sits'
sits_reduce(data, ...)

## S3 method for class 'raster_cube'
sits_reduce(
  data,
  ...,
  impute_fn = impute_linear(),
  memsize = 4L,
  multicores = 2L,
  output_dir,
  progress = FALSE
)

```

**Arguments**

data	Valid sits tibble or cube
...	Named expressions to be evaluated (see details).
impute_fn	Imputation function to remove NA values.
memsize	Memory available for classification (in GB).
multicores	Number of cores to be used for classification.
output_dir	Directory where files will be saved.
progress	Show progress bar?

**Details**

sits\_reduce() allows valid R expression to compute new bands. Use R syntax to pass an expression to this function. Besides arithmetic operators, you can use virtually any R function that can be applied to elements of a matrix. The provided functions must operate at line level in order to perform temporal reduction on a pixel.

sits\_reduce() Applies a function to each row of a matrix. In this matrix, each row represents a pixel and each column represents a single date. We provide some operations already implemented in the package to perform the reduce operation. See the list of available functions below:

**Value**

A sits tibble or a sits cube with new bands, produced according to the requested expression.

**Summarizing temporal functions**

- t\_max(): Returns the maximum value of the series.
- t\_min(): Returns the minimum value of the series
- t\_mean(): Returns the mean of the series.
- t\_median(): Returns the median of the series.
- t\_sum(): Returns the sum of all the points in the series.
- t\_std(): Returns the standard deviation of the series.
- t\_skewness(): Returns the skewness of the series.
- t\_kurtosis(): Returns the kurtosis of the series.
- t\_amplitude(): Returns the difference between the maximum and minimum values of the cycle. A small amplitude means a stable cycle.
- t\_fslope(): Returns the maximum value of the first slope of the cycle. Indicates when the cycle presents an abrupt change in the curve. The slope between two values relates the speed of the growth or senescence phases
- t\_mse(): Returns the average spectral energy density. The energy of the time series is distributed by frequency.
- t\_fqr(): Returns the value of the first quartile of the series (0.25).
- t\_tqr(): Returns the value of the third quartile of the series (0.75).
- t\_iqr(): Returns the interquartile range (difference between the third and first quartiles).

**Note**

The `t_sum()`, `t_std()`, `t_skewness()`, `t_kurtosis`, `t_mse` indexes generate values greater than the limit of a two-byte integer. Therefore, we save the images generated by these as Float-32 with no scale.

**Author(s)**

Felipe Carvalho, <felipe.carvalho@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # Reduce summarization function

  point2 <-
    sits_select(point_mt_6bands, "NDVI") |>
    sits_reduce(NDVI_MEDIAN = t_median(NDVI))

  # Example of generation mean summarization from a cube
  # Create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )

  # Reduce NDVI band with mean function
  cube_mean <- sits_reduce(
    data = cube,
    NDVIMEAN = t_mean(NDVI),
    output_dir = tempdir()
  )
}
```

---

sits\_reduce\_imbalance *Reduce imbalance in a set of samples*

---

**Description**

Takes a sits tibble with different labels and returns a new tibble. Deals with class imbalance using the synthetic minority oversampling technique (SMOTE) for oversampling. Undersampling is done using the SOM methods available in the sits package.

**Usage**

```
sits_reduce_imbalance(
  samples,
  n_samples_over = 200,
  n_samples_under = 400,
  multicores = 2
)
```

**Arguments**

<code>samples</code>	Sample set to rebalance
<code>n_samples_over</code>	Number of samples to oversample for classes with samples less than this number.
<code>n_samples_under</code>	Number of samples to undersample for classes with samples more than this number.
<code>multicores</code>	Number of cores to process the data (default 2).

**Value**

A sits tibble with reduced sample imbalance.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**References**

The reference paper on SMOTE is N. V. Chawla, K. W. Bowyer, L. O'Hall, W. P. Kegelmeyer, "SMOTE: synthetic minority over-sampling technique," Journal of artificial intelligence research, 321-357, 2002.

Undersampling uses the SOM map developed by Lorena Santos and co-workers and used in the `sits_som_map()` function. The SOM map technique is described in the paper: Lorena Santos, Karine Ferreira, Gilberto Camara, Michelle Picoli, Rolf Simoes, "Quality control and class noise reduction of satellite image time series". ISPRS Journal of Photogrammetry and Remote Sensing, vol. 177, pp 75-88, 2021. <https://doi.org/10.1016/j.isprsjprs.2021.04.014>.

**Examples**

```
if (sits_run_examples()) {
  # print the labels summary for a sample set
  summary(samples_modis_ndvi)
  # reduce the sample imbalance
  new_samples <- sits_reduce_imbalance(samples_modis_ndvi,
    n_samples_over = 200,
    n_samples_under = 200,
    multicores = 1
  )
  # print the labels summary for the rebalanced set
```

```

        summary(new_samples)
    }

```

---

sits\_regularize      *Build a regular data cube from an irregular one*

---

### Description

Produces regular data cubes for analysis-ready data (ARD) image collections. Analysis-ready data (ARD) collections available in AWS, MPC, USGS and DEAfrica are not regular in space and time. Bands may have different resolutions, images may not cover the entire time, and time intervals are not regular. For this reason, subsets of these collection need to be converted to regular data cubes before further processing and data analysis. This function requires users to include the cloud band in their ARD-based data cubes.

### Usage

```

sits_regularize(
  cube,
  ...,
  period,
  res,
  output_dir,
  roi = NULL,
  tiles = NULL,
  multicores = 2L,
  progress = TRUE
)

## S3 method for class 'raster_cube'
sits_regularize(
  cube,
  ...,
  period,
  res,
  output_dir,
  roi = NULL,
  multicores = 2L,
  progress = TRUE
)

## S3 method for class 'sar_cube'
sits_regularize(
  cube,
  ...,
  period,
  res,

```

```

    output_dir,
    roi = NULL,
    tiles = NULL,
    multicores = 2L,
    progress = TRUE
)

## S3 method for class 'derived_cube'
sits_regularize(cube, ...)

## Default S3 method:
sits_regularize(cube, ...)

```

### Arguments

<code>cube</code>	raster_cube object whose observation period and/or spatial resolution is not constant.
<code>...</code>	Additional parameters for <code>fn_check</code> function.
<code>period</code>	ISO8601-compliant time period for regular data cubes, with number and unit, where "D", "M" and "Y" stand for days, month and year; e.g., "P16D" for 16 days.
<code>res</code>	Spatial resolution of regularized images (in meters).
<code>output_dir</code>	Valid directory for storing regularized images.
<code>roi</code>	A named numeric vector with a region of interest.
<code>tiles</code>	MGRS tiles to be produced (only for Sentinel-1 cubes)
<code>multicores</code>	Number of cores used for regularization; used for parallel processing of input (integer)
<code>progress</code>	show progress bar?

### Value

A raster\_cube object with aggregated images.

### Note

The "roi" parameter defines a region of interest. It can be an `sf_object`, a shapefile, or a bounding box vector with named XY values ("xmin", "xmax", "ymin", "ymax") or named lat/long values ("lat\_min", "lat\_max", "long\_min", "long\_max"). `sits_regularize()` function will crop the images that contain the region of interest().

The aggregation method used in `sits_regularize` sorts the images based on cloud cover, where images with the fewest clouds at the top of the stack. Once the stack of images is sorted, the method uses the first valid value to create the temporal aggregation.

The input (non-regular) ARD cube needs to include the cloud band for the regularization to work.

### References

Appel, Marius; Pebesma, Edzer. On-demand processing of data cubes from satellite image collections with the `gdalcubes` library. *Data*, v. 4, n. 3, p. 92, 2019. DOI: 10.3390/data4030092.

**Examples**

```

if (sits_run_examples()) {
  # define a non-regular Sentinel-2 cube in AWS
  s2_cube_open <- sits_cube(
    source = "AWS",
    collection = "SENTINEL-2-L2A",
    tiles = c("20LKP", "20LLP"),
    bands = c("B8A", "CLOUD"),
    start_date = "2018-10-01",
    end_date = "2018-11-01"
  )
  # regularize the cube
  rg_cube <- sits_regularize(
    cube = s2_cube_open,
    period = "P16D",
    res = 60,
    multicores = 2,
    output_dir = tempdir()
  )

  ## Sentinel-1 SAR
  roi <- c("lon_min" = -50.410, "lon_max" = -50.379,
          "lat_min" = -10.1910, "lat_max" = -10.1573)
  s1_cube_open <- sits_cube(
    source = "MPC",
    collection = "SENTINEL-1-GRD",
    bands = c("VV", "VH"),
    orbit = "descending",
    roi = roi,
    start_date = "2020-06-01",
    end_date = "2020-09-28"
  )
  # regularize the cube
  rg_cube <- sits_regularize(
    cube = s1_cube_open,
    period = "P12D",
    res = 60,
    roi = roi,
    multicores = 2,
    output_dir = tempdir()
  )
}

```

sits\_resnet

*Train ResNet classification models***Description**

Use a ResNet architecture for classifying image time series. The ResNet (or deep residual network) was proposed by a team in Microsoft Research for 2D image classification. ResNet tries to address

the degradation of accuracy in a deep network. The idea is to replace a deep network with a combination of shallow ones. In the paper by Fawaz et al. (2019), ResNet was considered the best method for time series classification, using the UCR dataset. Please refer to the paper for more details.

The R-torch version is based on the code made available by Zhiguang Wang, author of the original paper. The code was developed in python using keras.

<https://github.com/cauchyturing> (repo: UCR\_Time\_Series\_Classification\_Deep\_Learning\_Baseline)

The R-torch version also considered the code by Ignacio Oguiza, whose implementation is available at <https://github.com/timeseriesAI/tsai/blob/main/tsai/models/ResNet.py>.

There are differences between Wang's Keras code and Oguiza torch code. In this case, we have used Wang's keras code as the main reference.

## Usage

```
sits_resnet(
  samples = NULL,
  samples_validation = NULL,
  blocks = c(64, 128, 128),
  kernels = c(7, 5, 3),
  epochs = 100,
  batch_size = 64,
  validation_split = 0.2,
  optimizer = torch::optim_adamw,
  opt_hparams = list(lr = 0.001, eps = 1e-08, weight_decay = 1e-06),
  lr_decay_epochs = 1,
  lr_decay_rate = 0.95,
  patience = 20,
  min_delta = 0.01,
  verbose = FALSE
)
```

## Arguments

<code>samples</code>	Time series with the training samples.
<code>samples_validation</code>	Time series with the validation samples. if the <code>samples_validation</code> parameter is provided, the <code>validation_split</code> parameter is ignored.
<code>blocks</code>	Number of 1D convolutional filters for each block of three layers.
<code>kernels</code>	Size of the 1D convolutional kernels
<code>epochs</code>	Number of iterations to train the model. for each layer of each block.
<code>batch_size</code>	Number of samples per gradient update.
<code>validation_split</code>	Fraction of training data to be used as validation data.
<code>optimizer</code>	Optimizer function to be used.
<code>opt_hparams</code>	Hyperparameters for optimizer: <code>lr</code> : Learning rate of the optimizer <code>eps</code> : Term added to the denominator to improve numerical stability. <code>weight_decay</code> : L2 regularization



lr_decay_epochs	Number of epochs to reduce learning rate.
lr_decay_rate	Decay factor for reducing learning rate.
patience	Number of epochs without improvements until training stops.
min_delta	Minimum improvement in loss function to reset the patience counter.
verbose	Verbosity mode (TRUE/FALSE). Default is FALSE.

**Value**

A fitted model to be used for classification.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Souza, <lipecaso@gmail.com>

Alber Sanchez, <alber.ipia@inpe.br>

Charlotte Pelletier, <charlotte.pelletier@univ-ubs.fr>

Daniel Falbel, <dfalbel@gmail.com>

**References**

Hassan Fawaz, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller, "Deep learning for time series classification: a review", *Data Mining and Knowledge Discovery*, 33(4): 917–963, 2019.

Zhiguang Wang, Weizhong Yan, and Tim Oates, "Time series classification from scratch with deep neural networks: A strong baseline", 2017 international joint conference on neural networks (IJCNN).

**Examples**

```
if (sits_run_examples()) {
  # create a ResNet model
  torch_model <- sits_train(samples_modis_ndvi, sits_resnet())
  # plot the model
  plot(torch_model)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
}
```

```

# classify a data cube
probs_cube <- sits_classify(
  data = cube, ml_model = torch_model, output_dir = tempdir()
)
# plot the probability cube
plot(probs_cube)
# smooth the probability cube using Bayesian statistics
bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
# plot the smoothed cube
plot(bayes_cube)
# label the probability cube
label_cube <- sits_label_classification(
  bayes_cube,
  output_dir = tempdir()
)
# plot the labelled cube
plot(label_cube)
}

```

---

sits\_rfor

*Train random forest models*


---

## Description

Use Random Forest algorithm to classify samples. This function is a front-end to the `randomForest` package. Please refer to the documentation in that package for more details.

## Usage

```
sits_rfor(samples = NULL, num_trees = 100, mtry = NULL, ...)
```

## Arguments

<code>samples</code>	Time series with the training samples (tibble of class "sits").
<code>num_trees</code>	Number of trees to grow. This should not be set to too small a number, to ensure that every input row gets predicted at least a few times (default: 100) (integer, min = 50, max = 150).
<code>mtry</code>	Number of variables randomly sampled as candidates at each split (default: NULL - use default value of <code>randomForest::randomForest()</code> function, i.e. <code>floor(sqrt(features))</code> ).
<code>...</code>	Other parameters to be passed to 'randomForest::randomForest' function.

## Value

Model fitted to input data (to be passed to `sits_classify`).

**Author(s)**

Alexandre Ywata de Carvalho, <alexandre.ywata@ipea.gov.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```
if (sits_run_examples()) {  
  # Example of training a model for time series classification  
  # Retrieve the samples for Mato Grosso  
  # train a random forest model  
  rf_model <- sits_train(samples_modis_ndvi,  
    ml_method = sits_rfor  
  )  
  # classify the point  
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")  
  # classify the point  
  point_class <- sits_classify(  
    data = point_ndvi, ml_model = rf_model  
  )  
  plot(point_class)  
}
```

---

sits\_run\_examples      *Informs if sits examples should run*

---

**Description**

This function informs if sits examples should run. To run the examples, set "SITS\_RUN\_EXAMPLES" to "YES" using `Sys.setenv("SITS_RUN_EXAMPLES" = "YES")` To come back to the default behaviour, please set `Sys.setenv("SITS_RUN_EXAMPLES" = "NO")`

**Usage**

```
sits_run_examples()
```

**Value**

A logical value

---

sits_run_tests	<i>Informs if sits tests should run</i>
----------------	---

---

**Description**

To run the tests, set "SITS\_RUN\_TESTS" environment to "YES" using `Sys.setenv("SITS_RUN_TESTS" = "YES")` To come back to the default behaviour, please set `Sys.setenv("SITS_RUN_TESTS" = "NO")`

**Usage**

```
sits_run_tests()
```

**Value**

TRUE/FALSE

---

sits_sample	<i>Sample a percentage of a time series</i>
-------------	---

---

**Description**

Takes a sits tibble with different labels and returns a new tibble. For a given field as a group criterion, this new tibble contains a percentage of the total number of samples per group. If `frac > 1`, all sampling will be done with replacement.

**Usage**

```
sits_sample(data, frac = 0.2, oversample = TRUE)
```

**Arguments**

data	Sits time series tibble (class = "sits")
frac	Percentage of samples to extract (range: 0.0 to 2.0, default = 0.2)
oversample	Logical: oversample classes with small number of samples? (TRUE/FALSE)

**Value**

A sits tibble with a fixed quantity of samples.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

## Examples

```
# Retrieve a set of time series with 2 classes
data(cerrado_2classes)
# Print the labels of the resulting tibble
summary(cerrado_2classes)
# Sample by fraction
data_02 <- sits_sample(cerrado_2classes, frac = 0.2)
# Print the labels
summary(data_02)
```

---

sits\_sampling\_design *Allocation of sample size to strata*

---

## Description

Takes a class cube with different labels and allocates a number of sample sizes per strata to obtain suitable values of error-adjusted area, providing five allocation strategies.

## Usage

```
sits_sampling_design(
  cube,
  expected_ua = 0.75,
  std_err = 0.01,
  rare_class_prop = 0.1
)
```

## Arguments

cube	Classified cube
expected_ua	Expected values of user's accuracy
std_err	Standard error we would like to achieve
rare_class_prop	Proportional area limit for rare classes

## Value

A matrix with options to decide allocation of sample size to each class. This matrix uses the same format as Table 5 of Olofsson et al.(2014).

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

## References

- [1] Olofsson, P., Foody, G.M., Stehman, S.V., Woodcock, C.E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, 129, pp.122-131.
- [2] Olofsson, P., Foody G.M., Herold M., Stehman, S.V., Woodcock, C.E., Wulder, M.A. (2014) Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, pp. 42-57.

## Examples

```
if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # estimated UA for classes
  expected_ua <- c(Cerrado = 0.75, Forest = 0.9,
                  Pasture = 0.8, Soy_Corn = 0.8)
  sampling_design <- sits_sampling_design(label_cube, expected_ua)
}
```

---

sits\_segment

*Segment an image*

---

## Description

Apply a spatial-temporal segmentation on a data cube based on a user defined segmentation function. The function applies the segmentation algorithm "seg\_fn" to each tile.

Segmentation uses the following steps:

1. Create a regular data cube with [sits\\_cube](#) and [sits\\_regularize](#);
2. Run [sits\\_segment](#) to obtain a vector data cube with polygons that define the boundary of the segments;

3. Classify the time series associated to the segments with `sits_classify`, to get obtain a vector probability cube;
4. Use `sits_label_classification` to label the vector probability cube;
5. Display the results with `plot` or `sits_view`.

### Usage

```
sits_segment(
  cube,
  seg_fn = sits_slic(),
  roi = NULL,
  impute_fn = impute_linear(),
  start_date = NULL,
  end_date = NULL,
  memsize = 8,
  multicores = 2,
  output_dir,
  version = "v1",
  progress = TRUE
)
```

### Arguments

<code>cube</code>	Regular data cube
<code>seg_fn</code>	Function to apply the segmentation
<code>roi</code>	Region of interest (see below)
<code>impute_fn</code>	Imputation function to remove NA values.
<code>start_date</code>	Start date for the segmentation
<code>end_date</code>	End date for the segmentation.
<code>memsize</code>	Memory available for classification (in GB).
<code>multicores</code>	Number of cores to be used for classification.
<code>output_dir</code>	Directory for output file.
<code>version</code>	Version of the output (for multiple segmentations).
<code>progress</code>	Show progress bar?

### Value

A tibble of class 'segs\_cube' representing the segmentation.

### Note

The "roi" parameter defines a region of interest. It can be an `sf_object`, a shapefile, or a bounding box vector with named XY values ("xmin", "xmax", "ymin", "ymax") or named lat/long values ("lon\_min", "lat\_min", "lon\_max", "lat\_max")

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Carvalho, <felipe.carvalho@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  # create a data cube
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # segment the vector cube
  segments <- sits_segment(
    cube = cube,
    output_dir = tempdir()
  )
  # create a classification model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify the segments
  seg_probs <- sits_classify(
    data = segments,
    ml_model = rfor_model,
    output_dir = tempdir()
  )
  # label the probability segments
  seg_label <- sits_label_classification(
    cube = seg_probs,
    output_dir = tempdir()
  )
}
```

---

sits\_select

*Filter bands on a data set (tibble or cube)*

---

**Description**

Filter only the selected bands and dates from a set of time series or from a data cube.

**Usage**

```
sits_select(data, bands = NULL, start_date = NULL, end_date = NULL, ...)
```

```
## S3 method for class 'sits'
```

```
sits_select(data, bands = NULL, start_date = NULL, end_date = NULL, ...)
```



```
## S3 method for class 'raster_cube'
sits_select(
  data,
  bands = NULL,
  start_date = NULL,
  end_date = NULL,
  ...,
  dates = NULL,
  tiles = NULL
)

## S3 method for class 'patterns'
sits_select(data, bands = NULL, start_date = NULL, end_date = NULL, ...)

## Default S3 method:
sits_select(data, ...)
```

### Arguments

data	Tibble with time series or data cube.
bands	Character vector with the names of the bands.
start_date	Date in YYYY-MM-DD format: start date to be filtered.
end_date	Date in YYYY-MM-DD format: end date to be filtered.
...	Additional parameters to be provided
dates	Character vector with sparse dates to select.
tiles	Character vector with the names of the tiles.

### Value

Tibble with time series or data cube.

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

### Examples

```
# Retrieve a set of time series with 2 classes
data(cerrado_2classes)
# Print the original bands
sits_bands(cerrado_2classes)
# Select only the NDVI band
data <- sits_select(cerrado_2classes, bands = c("NDVI"))
# Print the labels of the resulting tibble
sits_bands(data)
# select start and end date
point_2010 <- sits_select(point_mt_6bands,
```

```
start_date = "2000-01-01",  
end_date = "2030-12-31")
```

---

sits\_sgolay

*Filter time series with Savitzky-Golay filter*

---

### Description

An optimal polynomial for warping a time series. The degree of smoothing depends on the filter order (usually 3.0). The order of the polynomial uses the parameter 'order' (default = 3), the size of the temporal window uses the parameter 'length' (default = 5).

### Usage

```
sits_sgolay(data = NULL, order = 3, length = 5)
```

### Arguments

data	Time series or matrix.
order	Filter order (integer).
length	Filter length (must be odd).

### Value

Filtered time series

### Author(s)

Rolf Simoes, <rolf.simoese@inpe.br>  
Gilberto Camara, <gilberto.camara@inpe.br>  
Felipe Carvalho, <felipe.carvalho@inpe.br>

### References

A. Savitzky, M. Golay, "Smoothing and Differentiation of Data by Simplified Least Squares Procedures". Analytical Chemistry, 36 (8): 1627–39, 1964.

### Examples

```
if (sits_run_examples()) {  
  # Retrieve a time series with values of NDVI  
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")  
  
  # Filter the point using the Savitzky-Golay smoother  
  point_sg <- sits_filter(point_ndvi,  
    filter = sits_sgolay(order = 3, length = 5)  
  )  
}
```

```

# Merge time series
point_ndvi <- sits_merge(point_ndvi, point_sg, suffix = c("", ".SG"))

# Plot the two points to see the smoothing effect
plot(point_ndvi)
}

```

---

sits\_slic

*Segment an image using SLIC*


---

### Description

Apply a segmentation on a data cube based on the supercells package. This is an adaptation and extension to remote sensing data of the SLIC superpixels algorithm proposed by Achanta et al. (2012). See references for more details.

### Usage

```

sits_slic(
  data = NULL,
  step = 5,
  compactness = 1,
  dist_fun = "euclidean",
  avg_fun = "median",
  iter = 30,
  minarea = 10,
  verbose = FALSE
)

```

### Arguments

<code>data</code>	A matrix with time series.
<code>step</code>	Distance (in number of cells) between initial supercells' centers.
<code>compactness</code>	A compactness value. Larger values cause clusters to be more compact/even (square).
<code>dist_fun</code>	Distance function. Currently implemented: euclidean, jsd, dtw, and any distance function from the <code>philentropy</code> package. See <code>philentropy::getDistMethods()</code> .
<code>avg_fun</code>	Averaging function to calculate the values of the supercells' centers. Accepts any fitting R function (e.g., <code>base::mean()</code> or <code>stats::median()</code> ) or one of internally implemented "mean" and "median". Default: "median"
<code>iter</code>	Number of iterations to create the output.
<code>minarea</code>	Specifies the minimal size of a supercell (in cells).
<code>verbose</code>	Show the progress bar?

### Value

Set of segments for a single tile

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Carvalho, <felipe.carvalho@inpe.br>

**References**

Achanta, Radhakrishna, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, and Sabine Süsstrunk. 2012. "SLIC Superpixels Compared to State-of-the-Art Superpixel Methods." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 34 (11): 2274–82.

Nowosad, Jakub, and Tomasz F. Stepinski. 2022. "Extended SLIC Superpixels Algorithm for Applications to Non-Imagery Geospatial Rasters." *International Journal of Applied Earth Observation and Geoinformation* 112 (August): 102935.

**Examples**

```
if (sits_run_examples()) {
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  # create a data cube
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # segment the vector cube
  segments <- sits_segment(
    cube = cube,
    output_dir = tempdir(),
    version = "slic-demo"
  )
  # create a classification model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify the segments
  seg_probs <- sits_classify(
    data = segments,
    ml_model = rfor_model,
    output_dir = tempdir(),
    version = "slic-demo"
  )
  # label the probability segments
  seg_label <- sits_label_classification(
    cube = seg_probs,
    output_dir = tempdir(),
    version = "slic-demo"
  )
}
```

---

`sits_smooth`*Smooth probability cubes with spatial predictors*

---

**Description**

Takes a set of classified raster layers with probabilities, whose metadata is created by `sits_cube`, and applies a Bayesian smoothing function.

**Usage**

```
sits_smooth(  
  cube,  
  window_size = 7L,  
  neigh_fraction = 0.5,  
  smoothness = 10L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)  
  
## S3 method for class 'probs_cube'  
sits_smooth(  
  cube,  
  window_size = 7L,  
  neigh_fraction = 0.5,  
  smoothness = 10L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)  
  
## S3 method for class 'raster_cube'  
sits_smooth(  
  cube,  
  window_size = 7L,  
  neigh_fraction = 0.5,  
  smoothness = 10L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)  
  
## S3 method for class 'derived_cube'  
sits_smooth(  
  cube,  
  window_size = 7L,  
  neigh_fraction = 0.5,  
  smoothness = 10L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)
```

```
cube,  
window_size = 7L,  
neigh_fraction = 0.5,  
smoothness = 10L,  
memsize = 4L,  
multicores = 2L,  
output_dir,  
version = "v1"  
)  
  
## Default S3 method:  
sits_smooth(  
  cube,  
  window_size = 7L,  
  neigh_fraction = 0.5,  
  smoothness = 10L,  
  memsize = 4L,  
  multicores = 2L,  
  output_dir,  
  version = "v1"  
)
```

### Arguments

cube	Probability data cube.
window_size	Size of the neighborhood (integer, min = 3, max = 21)
neigh_fraction	Fraction of neighbors with high probabilities to be used in Bayesian inference. (numeric, min = 0.1, max = 1.0)
smoothness	Estimated variance of logit of class probabilities (Bayesian smoothing parameter) (integer vector or scalar, min = 1, max = 200).
memsize	Memory available for classification in GB (integer, min = 1, max = 16384).
multicores	Number of cores to be used for classification (integer, min = 1, max = 2048).
output_dir	Valid directory for output file. (character vector of length 1).
version	Version of the output (character vector of length 1).

### Value

A data cube.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

## Examples

```

if (sits_run_examples()) {
  # create an xgboost model
  xgb_model <- sits_train(samples_modis_ndvi, sits_xgboost())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = xgb_model, output_dir = tempdir()
  )
  # plot the probability cube
  plot(probs_cube)
  # smooth the probability cube using Bayesian statistics
  bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
  # plot the smoothed cube
  plot(bayes_cube)
  # label the probability cube
  label_cube <- sits_label_classification(
    bayes_cube,
    output_dir = tempdir()
  )
  # plot the labelled cube
  plot(label_cube)
}

```

---

sits\_som

*Use SOM for quality analysis of time series samples*


---

## Description

These functions use self-organized maps to perform quality analysis in satellite image time series.

`sits_som_map()` creates a SOM map, where high-dimensional data is mapped into a two-dimensional map, keeping the topological relations between data patterns. Each sample is assigned to a neuron, and neurons are placed in the grid based on similarity.

`sits_som_evaluate_cluster()` analyses the neurons of the SOM map, and builds clusters based on them. Each cluster is a neuron or a set of neurons categorized with the same label. It produces a tibble with the percentage of mixture of classes in each cluster.

`sits_som_clean_samples()` evaluates the quality of the samples based on the results of the SOM map. The algorithm identifies noisy samples, using 'prior\_threshold' for the prior probability and 'posterior\_threshold' for the posterior probability. Each sample receives an evaluation tag, according to the following rule: (a) If the prior probability is < 'prior\_threshold', the sample is tagged as "remove"; (b) If the prior probability is >= 'prior\_threshold' and the posterior probability is

$\geq$  'posterior\_threshold', the sample is tagged as "clean"; (c) If the prior probability is  $\geq$  'posterior\_threshold' and the posterior probability is  $<$  'posterior\_threshold', the sample is tagged as "analyze" for further inspection. The user can define which tagged samples will be returned using the "keep" parameter, with the following options: "clean", "analyze", "remove".

### Usage

```
sits_som_map(
  data,
  grid_xdim = 10,
  grid_ydim = 10,
  alpha = 1,
  rlen = 100,
  distance = "dtw",
  som_radius = 2,
  mode = "online"
)
```

### Arguments

data	A tibble with samples to be clustered.
grid_xdim	X dimension of the SOM grid (default = 25).
grid_ydim	Y dimension of the SOM grid.
alpha	Starting learning rate (decreases according to number of iterations).
rlen	Number of iterations to produce the SOM.
distance	The type of similarity measure (distance). The following similarity measurements are supported: "euclidean" and "dtw". The default similarity measure is "dtw".
som_radius	Radius of SOM neighborhood.
mode	Type of learning algorithm. The following learning algorithms are available: "online", "batch", and "pbatch". The default learning algorithm is "online".

### Value

sits\_som\_map() produces a list with three members: (1) the samples tibble, with one additional column indicating to which neuron each sample has been mapped; (2) the Kohonen map, used for plotting and cluster quality measures; (3) a tibble with the labelled neurons, where each class of each neuron is associated to two values: (a) the prior probability that this class belongs to a cluster based on the frequency of samples of this class allocated to the neuron; (b) the posterior probability that this class belongs to a cluster, using data for the neighbours on the SOM map.

### Note

To learn more about the learning algorithms, check the [kohonen::supersom](#) function.

The sits package implements the "dtw" (Dynamic Time Warping) similarity measure. The "euclidean" similarity measurement come from the [kohonen::supersom\(dist.fcts\)](#) function.



**Author(s)**

Lorena Alves, <lorena.santos@inpe.br>

Karine Ferreira. <karine.ferreira@inpe.br>

**References**

Lorena Santos, Karine Ferreira, Gilberto Camara, Michelle Picoli, Rolf Simoes, “Quality control and class noise reduction of satellite image time series”. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 177, pp 75-88, 2021. <https://doi.org/10.1016/j.isprsjprs.2021.04.014>.

**Examples**

```
if (sits_run_examples()) {  
  # create a som map  
  som_map <- sits_som_map(samples_modis_ndvi)  
  # plot the som map  
  plot(som_map)  
  # evaluate the som map and create clusters  
  clusters_som <- sits_som_evaluate_cluster(som_map)  
  # plot the cluster evaluation  
  plot(clusters_som)  
  # clean the samples  
  new_samples <- sits_som_clean_samples(som_map)  
}
```

---

sits\_som\_clean\_samples

*Cleans the samples based on SOM map information*

---

**Description**

Cleans the samples based on SOM map information

**Usage**

```
sits_som_clean_samples(  
  som_map,  
  prior_threshold = 0.6,  
  posterior_threshold = 0.6,  
  keep = c("clean", "analyze")  
)
```

**Arguments**

som_map	Returned by <code>sits_som_map</code> .
prior_threshold	Threshold of conditional probability (frequency of samples assigned to the same SOM neuron).
posterior_threshold	Threshold of posterior probability (influenced by the SOM neighborhood).
keep	Which types of evaluation to be maintained in the data.

**Value**

tibble with an two additional columns. The first indicates if each sample is clean, should be analyzed or should be removed. The second is the posterior probability of the sample.

**Examples**

```
if (sits_run_examples()) {
  # create a som map
  som_map <- sits_som_map(samples_modis_ndvi)
  # plot the som map
  plot(som_map)
  # evaluate the som map and create clusters
  clusters_som <- sits_som_evaluate_cluster(som_map)
  # plot the cluster evaluation
  plot(clusters_som)
  # clean the samples
  new_samples <- sits_som_clean_samples(som_map)
}
```

---

sits\_som\_evaluate\_cluster

*Evaluate cluster*

---

**Description**

`sits_som_evaluate_cluster()` produces a tibble with the clusters found by the SOM map. For each cluster, it provides the percentage of classes inside it.

**Usage**

```
sits_som_evaluate_cluster(som_map)
```

**Arguments**

som_map	A SOM map produced by the <code>som_map()</code> function
---------	---

**Value**

A tibble stating the purity for each cluster

**Examples**

```
if (sits_run_examples()) {  
  # create a som map  
  som_map <- sits_som_map(samples_modis_ndvi)  
  # plot the som map  
  plot(som_map)  
  # evaluate the som map and create clusters  
  clusters_som <- sits_som_evaluate_cluster(som_map)  
  # plot the cluster evaluation  
  plot(clusters_som)  
  # clean the samples  
  new_samples <- sits_som_clean_samples(som_map)  
}
```

---

sits\_stats

*Obtain statistics for all sample bands*

---

**Description**

Most machine learning algorithms require data to be normalized. This applies to the "SVM" method and to all deep learning ones. To normalize the predictors, it is necessary to extract the statistics of each band of the samples. This function computes the 2 of the distribution of each band of the samples. This values are used as minimum and maximum values in the normalization operation performed by the `sits_pred_normalize()` function.

**Usage**

```
sits_stats(samples)
```

**Arguments**

`samples` Time series samples uses as training data.

**Value**

A list with the 2 training data.

**Note**

Please refer to the sits documentation available in [<https://e-sensing.github.io/sitsbook/>](https://e-sensing.github.io/sitsbook/) for detailed examples.

**Author(s)**

Gilberto Camara, [<gilberto.camara@inpe.br>](mailto:gilberto.camara@inpe.br)

**Examples**

```
if (sits_run_examples()) {  
  stats <- sits_stats(samples_modis_ndvi)  
}
```

---

sits\_stratified\_sampling

*Allocation of sample size to strata*

---

**Description**

Takes a class cube with different labels and a sampling design with a number of samples per class and allocates a set of locations for each class

**Usage**

```
sits_stratified_sampling(  
  cube,  
  sampling_design,  
  alloc = "alloc_prop",  
  overhead = 1.2,  
  multicores = 2L,  
  shp_file = NULL,  
  progress = TRUE  
)
```

**Arguments**

cube	Classified cube
sampling_design	Result of sits_sampling_design
alloc	Allocation method chosen
overhead	Additional percentage to account for border points
multicores	Number of cores that will be used to sample the images in parallel.
shp_file	Name of shapefile to be saved (optional)
progress	Show progress bar? Default is TRUE.

**Value**

samples Point sf object with required samples

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```

if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # estimated UA for classes
  expected_ua <- c(Cerrado = 0.95, Forest = 0.95,
                  Pasture = 0.95, Soy_Corn = 0.95)
  # design sampling
  sampling_design <- sits_sampling_design(label_cube, expected_ua)
  # select samples
  samples <- sits_stratified_sampling(label_cube,
                                     sampling_design, "alloc_prop")
}

```

---

sits\_svm

*Train support vector machine models*


---

## Description

This function receives a tibble with a set of attributes X for each observation Y. These attributes are the values of the time series for each band. The SVM algorithm is used for multiclass-classification. For this purpose, it uses the "one-against-one" approach, in which  $k(k-1)/2$  binary classifiers are trained; the appropriate class is found by a voting scheme. This function is a front-end to the "svm" method in the "e1071" package. Please refer to the documentation in that package for more details.

## Usage

```

sits_svm(
  samples = NULL,
  formula = sits_formula_linear(),
  scale = FALSE,
  cachesize = 1000,

```

```

kernel = "radial",
degree = 3,
coef0 = 0,
cost = 10,
tolerance = 0.001,
epsilon = 0.1,
cross = 10,
...
)

```

### Arguments

samples	Time series with the training samples.
formula	Symbolic description of the model to be fit. (default: sits_formula_linear).
scale	Logical vector indicating the variables to be scaled.
cacheSize	Cache memory in MB (default = 1000).
kernel	Kernel used in training and predicting. options: "linear", "polynomial", "radial", "sigmoid" (default: "radial").
degree	Exponential of polynomial type kernel (default: 3).
coef0	Parameter needed for kernels of type polynomial and sigmoid (default: 0).
cost	Cost of constraints violation (default: 10).
tolerance	Tolerance of termination criterion (default: 0.001).
epsilon	Epsilon in the insensitive-loss function (default: 0.1).
cross	Number of cross validation folds applied to assess the quality of the model (default: 10).
...	Other parameters to be passed to e1071::svm function.

### Value

Model fitted to input data (to be passed to [sits\\_classify](#))

### Note

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

### Author(s)

Alexandre Ywata de Carvalho, <[alexandre.ywata@ipea.gov.br](mailto:alexandre.ywata@ipea.gov.br)>

Rolf Simoes, <[rolf.simoes@inpe.br](mailto:rolf.simoes@inpe.br)>

Gilberto Camara, <[gilberto.camara@inpe.br](mailto:gilberto.camara@inpe.br)>

**Examples**

```

if (sits_run_examples()) {
  # Example of training a model for time series classification
  # Retrieve the samples for Mato Grosso
  # train an SVM model
  ml_model <- sits_train(samples_modis_ndvi, ml_method = sits_svm)
  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  # classify the point
  point_class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
  plot(point_class)
}

```

---

sits\_tae

*Train a model using Temporal Self-Attention Encoder*


---

**Description**

Implementation of Temporal Attention Encoder (TAE) for satellite image time series classification.

This function is based on the paper by Vivien Garnot referenced below and code available on github at <https://github.com/VSainteuf/pytorch-psetae>.

We also used the code made available by Maja Schneider in her work with Marco Körner referenced below and available at <https://github.com/maja601/RC2020-psetae>.

If you use this method, please cite Garnot's and Schneider's work.

**Usage**

```

sits_tae(
  samples = NULL,
  samples_validation = NULL,
  epochs = 150,
  batch_size = 64,
  validation_split = 0.2,
  optimizer = torchopt::optim_adamw,
  opt_hparams = list(lr = 0.001, eps = 1e-08, weight_decay = 1e-06),
  lr_decay_epochs = 1,
  lr_decay_rate = 0.95,
  patience = 20,
  min_delta = 0.01,
  verbose = FALSE
)

```

**Arguments**

<code>samples</code>	Time series with the training samples.
<code>samples_validation</code>	Time series with the validation samples. if the <code>samples_validation</code> parameter is provided, the <code>validation_split</code> parameter is ignored.
<code>epochs</code>	Number of iterations to train the model.
<code>batch_size</code>	Number of samples per gradient update.
<code>validation_split</code>	Number between 0 and 1. Fraction of training data to be used as validation data.
<code>optimizer</code>	Optimizer function to be used.
<code>opt_hparams</code>	Hyperparameters for optimizer: <code>lr</code> : Learning rate of the optimizer <code>eps</code> : Term added to the denominator to improve numerical stability. <code>weight_decay</code> : L2 regularization
<code>lr_decay_epochs</code>	Number of epochs to reduce learning rate.
<code>lr_decay_rate</code>	Decay factor for reducing learning rate.
<code>patience</code>	Number of epochs without improvements until training stops.
<code>min_delta</code>	Minimum improvement to reset the patience counter.
<code>verbose</code>	Verbosity mode (TRUE/FALSE). Default is FALSE.

**Value**

A fitted model to be used for classification.

**Author(s)**

Charlotte Pelletier, <charlotte.pelletier@univ-ubs.fr>

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**References**

Vivien Garnot, Loic Landrieu, Sebastien Giordano, and Nesrine Chehata, "Satellite Image Time Series Classification with Pixel-Set Encoders and Temporal Self-Attention", 2020 Conference on Computer Vision and Pattern Recognition. pages 12322-12331. DOI: 10.1109/CVPR42600.2020.01234

Schneider, Maja; Körner, Marco, "[Re] Satellite Image Time Series Classification with Pixel-Set Encoders and Temporal Self-Attention." *ReScience C* 7 (2), 2021. DOI: 10.5281/zenodo.4835356

**Examples**

```
if (sits_run_examples()) {
  # create a TAE model
  torch_model <- sits_train(samples_modis_ndvi, sits_tae())
  # plot the model
  plot(torch_model)
```



```

# create a data cube from local files
data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
cube <- sits_cube(
  source = "BDC",
  collection = "MOD13Q1-6",
  data_dir = data_dir
)
# classify a data cube
probs_cube <- sits_classify(
  data = cube, ml_model = torch_model, output_dir = tempdir()
)
# plot the probability cube
plot(probs_cube)
# smooth the probability cube using Bayesian statistics
bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
# plot the smoothed cube
plot(bayes_cube)
# label the probability cube
label_cube <- sits_label_classification(
  bayes_cube,
  output_dir = tempdir()
)
# plot the labelled cube
plot(label_cube)
}

```

---

sits\_tempcnn

*Train temporal convolutional neural network models*


---

## Description

Use a TempCNN algorithm to classify data, which has two stages: a 1D CNN and a multi-layer perceptron. Users can define the depth of the 1D network, as well as the number of perceptron layers.

This function is based on the paper by Charlotte Pelletier referenced below. If you use this method, please cite the original tempCNN paper.

The torch version is based on the code made available by the BreizhCrops team: Marc Russwurm, Charlotte Pelletier, Marco Korner, Maximilian Zollner. The original python code is available at the website <https://github.com/dl4sits/BreizhCrops>. This code is licensed as GPL-3.

## Usage

```

sits_tempcnn(
  samples = NULL,
  samples_validation = NULL,
  cnn_layers = c(256, 256, 256),
  cnn_kernels = c(5, 5, 5),
  cnn_dropout_rates = c(0.2, 0.2, 0.2),

```

```

dense_layer_nodes = 256,
dense_layer_dropout_rate = 0.5,
epochs = 150,
batch_size = 64,
validation_split = 0.2,
optimizer = torch::optim_adamw,
opt_hparams = list(lr = 0.005, eps = 1e-08, weight_decay = 1e-06),
lr_decay_epochs = 1,
lr_decay_rate = 0.95,
patience = 20,
min_delta = 0.01,
verbose = FALSE
)

```

### Arguments

<code>samples</code>	Time series with the training samples.
<code>samples_validation</code>	Time series with the validation samples. if the <code>samples_validation</code> parameter is provided, the <code>validation_split</code> parameter is ignored.
<code>cnn_layers</code>	Number of 1D convolutional filters per layer
<code>cnn_kernels</code>	Size of the 1D convolutional kernels.
<code>cnn_dropout_rates</code>	Dropout rates for 1D convolutional filters.
<code>dense_layer_nodes</code>	Number of nodes in the dense layer.
<code>dense_layer_dropout_rate</code>	Dropout rate (0,1) for the dense layer.
<code>epochs</code>	Number of iterations to train the model.
<code>batch_size</code>	Number of samples per gradient update.
<code>validation_split</code>	Fraction of training data to be used for validation.
<code>optimizer</code>	Optimizer function to be used.
<code>opt_hparams</code>	Hyperparameters for optimizer: <code>lr</code> : Learning rate of the optimizer <code>eps</code> : Term added to the denominator to improve numerical stability. <code>weight_decay</code> : L2 regularization
<code>lr_decay_epochs</code>	Number of epochs to reduce learning rate.
<code>lr_decay_rate</code>	Decay factor for reducing learning rate.
<code>patience</code>	Number of epochs without improvements until training stops.
<code>min_delta</code>	Minimum improvement in loss function to reset the patience counter.
<code>verbose</code>	Verbosity mode (TRUE/FALSE). Default is FALSE.

### Value

A fitted model to be used for classification.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Charlotte Pelletier, <charlotte.pelletier@univ-ubs.fr>

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Souza, <lipecaso@gmail.com>

**References**

Charlotte Pelletier, Geoffrey Webb and François Petitjean, "Temporal Convolutional Neural Network for the Classification of Satellite Image Time Series", *Remote Sensing*, 11,523, 2019. DOI: 10.3390/rs11050523.

**Examples**

```
if (sits_run_examples()) {
  # create a TempCNN model
  torch_model <- sits_train(samples_modis_ndvi, sits_tempcnn())
  # plot the model
  plot(torch_model)
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = torch_model, output_dir = tempdir()
  )
  # plot the probability cube
  plot(probs_cube)
  # smooth the probability cube using Bayesian statistics
  bayes_cube <- sits_smooth(probs_cube, output_dir = tempdir())
  # plot the smoothed cube
  plot(bayes_cube)
  # label the probability cube
  label_cube <- sits_label_classification(
    bayes_cube,
    output_dir = tempdir()
  )
  # plot the labelled cube
  plot(label_cube)
}
```

---

sits_timeline	<i>Get timeline of a cube or a set of time series</i>
---------------	---

---

### Description

This function returns the timeline for a given data set, either a set of time series, a data cube, or a trained model.

### Usage

```
sits_timeline(data)

## S3 method for class 'sits'
sits_timeline(data)

## S3 method for class 'sits_model'
sits_timeline(data)

## S3 method for class 'raster_cube'
sits_timeline(data)

## S3 method for class 'derived_cube'
sits_timeline(data)

## S3 method for class 'tbl_df'
sits_timeline(data)

## Default S3 method:
sits_timeline(data)
```

### Arguments

data            Tibble of class "sits" or class "raster\_cube"

### Value

Vector of class Date with timeline of samples or data cube.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

### Examples

```
sits_timeline(samples_modis_ndvi)
```

---

`sits_to_csv`*Export a sits tibble metadata to the CSV format*

---

## Description

Converts metadata from a sits tibble to a CSV file. The CSV file will not contain the actual time series. Its columns will be the same as those of a CSV file used to retrieve data from ground information ("latitude", "longitude", "start\_date", "end\_date", "cube", "label"). If the file is NULL, returns a data.frame as an object

## Usage

```
sits_to_csv(data, file = NULL)

## S3 method for class 'sits'
sits_to_csv(data, file = NULL)

## S3 method for class 'tbl_df'
sits_to_csv(data, file)

## Default S3 method:
sits_to_csv(data, file)
```

## Arguments

<code>data</code>	Time series (tibble of class "sits").
<code>file</code>	Full path of the exported CSV file (valid file name with extension ".csv").

## Value

Return data.frame with CSV columns (optional)

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```
csv_file <- paste0(tempdir(), "/cerrado_2classes.csv")
sits_to_csv(cerrado_2classes, file = csv_file)
```

---

`sits_to_xlsx`*Save accuracy assessments as Excel files*

---

### Description

Saves confusion matrices as Excel spreadsheets. This function takes the a list of accuracy assessments generated by `sits_accuracy` and saves them in an Excel spreadsheet.

### Usage

```
sits_to_xlsx(acc, file)

## S3 method for class 'sits_accuracy'
sits_to_xlsx(acc, file)

## S3 method for class 'list'
sits_to_xlsx(acc, file)
```

### Arguments

<code>acc</code>	Accuracy statistics (either an output of <code>sits_accuracy</code> or a list of those)
<code>file</code>	The file where the XLSX data is to be saved.

### Value

No return value, called for side effects.

### Note

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

### Examples

```
if (sits_run_examples()) {
  # A dataset containing a tibble with time series samples
  # for the Mato Grosso state in Brasil
  # create a list to store the results
  results <- list()

  # accuracy assessment lightTAE
  acc_ltae <- sits_kfold_validate(samples_modis_ndvi,
    folds = 5,
    multicores = 1,
```

```
      ml_method = sits_lighttae()
    )
    # use a name
    acc_ltae$name <- "LightTAE"

    # put the result in a list
    results[[length(results) + 1]] <- acc_ltae

    # save to xlsx file
    sits_to_xlsx(
      results,
      file = tempfile("accuracy_mato_grosso_dl_", fileext = ".xlsx")
    )
  }
}
```

---

sits\_train

*Train classification models*

---

## Description

Given a tibble with a set of distance measures, returns trained models. Currently, sits supports the following models: 'svm' (see [sits\\_svm](#)), random forests (see [sits\\_rfor](#)), extreme gradient boosting (see [sits\\_xgboost](#)), and different deep learning functions, including multi-layer perceptrons (see [sits\\_mlp](#)), 1D convolution neural networks [sits\\_tempcnn](#), deep residual networks [sits\\_resnet](#) and self-attention encoders [sits\\_lighttae](#)

## Usage

```
sits_train(samples, ml_method = sits_svm())
```

## Arguments

samples	Time series with the training samples.
ml_method	Machine learning method.

## Value

Model fitted to input data to be passed to [sits\\_classify](#)

## Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

Alexandre Ywata de Carvalho, <alexandre.ywata@ipea.gov.br>

## Examples

```
if (sits_run_examples()) {
  # Retrieve the set of samples for Mato Grosso
  # fit a training model (rfor model)
  ml_model <- sits_train(samples_modis_ndvi, sits_rfor(num_trees = 50))
  # get a point and classify the point with the ml_model
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
}
```

---

sits\_tuning

*Tuning machine learning models hyper-parameters*


---

## Description

Machine learning models use stochastic gradient descent (SGD) techniques to find optimal solutions. To perform SGD, models use optimization algorithms which have hyperparameters that have to be adjusted to achieve best performance for each application.

This function performs a random search on values of selected hyperparameters. Instead of performing an exhaustive test of all parameter combinations, it selecting them randomly. Validation is done using an independent set of samples or by a validation split. The function returns the best hyperparameters in a list. Hyper-parameters passed to params parameter should be passed by calling sits\_tuning\_hparams().

## Usage

```
sits_tuning(
  samples,
  samples_validation = NULL,
  validation_split = 0.2,
  ml_method = sits_tempcnn(),
  params = sits_tuning_hparams(optimizer = torchopt::optim_adamw, opt_hparams = list(lr =
    loguniform(10^-2, 10^-4))),
  trials = 30,
  multicores = 2,
  progress = FALSE
)
```

## Arguments

samples	Time series set to be validated.
samples_validation	Time series set used for validation.
validation_split	Percent of original time series set to be used for validation (if samples_validation is NULL)



ml_method	Machine learning method.
params	List with hyper parameters to be passed to ml_method. User can use uniform, choice, randint, normal, lognormal, loguniform, and beta distribution functions to randomize parameters.
trials	Number of random trials to perform the random search.
multicores	Number of cores to process in parallel
progress	Show progress bar?

**Value**

A tibble containing all parameters used to train on each trial ordered by accuracy

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

**References**

James Bergstra, Yoshua Bengio, "Random Search for Hyper-Parameter Optimization". Journal of Machine Learning Research. 13: 281–305, 2012.

**Examples**

```
if (sits_run_examples()) {
  # find best learning rate parameters for TempCNN
  tuned <- sits_tuning(
    samples_modis_ndvi,
    ml_method = sits_tempcnn(),
    params = sits_tuning_hparams(
      optimizer = choice(
        torch::optim_adamw
      ),
      opt_hparams = list(
        lr = loguniform(10^-2, 10^-4)
      )
    ),
    trials = 4,
    multicores = 2,
    progress = FALSE
  )
  # obtain best accuracy, kappa and best_lr
  accuracy <- tuned$accuracy[[1]]
  kappa <- tuned$kappa[[1]]
  best_lr <- tuned$opt_hparams[[1]]$lr
}
```

---

sits\_tuning\_hparams     *Tuning machine learning models hyper-parameters*

---

## Description

This function allow user building the hyper-parameters space used by `sits_tuning()` function search randomly the best parameter combination.

Users should pass the possible values for hyper-parameters as constants or by calling the following random functions:

- `uniform(min = 0, max = 1, n = 1)`: returns random numbers from a uniform distribution with parameters min and max.
- `choice(..., replace = TRUE, n = 1)`: returns random objects passed to ... with replacement or not (parameter replace).
- `randint(min, max, n = 1)`: returns random integers from a uniform distribution with parameters min and max.
- `normal(mean = 0, sd = 1, n = 1)`: returns random numbers from a normal distribution with parameters min and max.
- `lognormal(meanlog = 0, sdlog = 1, n = 1)`: returns random numbers from a lognormal distribution with parameters min and max.
- `loguniform(minlog = 0, maxlog = 1, n = 1)`: returns random numbers from a loguniform distribution with parameters min and max.
- `beta(shape1, shape2, n = 1)`: returns random numbers from a beta distribution with parameters min and max.

These functions accepts n parameter to indicate how many values should be returned.

## Usage

```
sits_tuning_hparams(...)
```

## Arguments

...                      Used to prepare hyper-parameter space

## Value

A list containing the hyper-parameter space to be passed to `sits_tuning()`'s `params` parameter.

## Examples

```
if (sits_run_examples()) {  
  # find best learning rate parameters for TempCNN  
  tuned <- sits_tuning(  
    samples_modis_ndvi,  
    ml_method = sits_tempcnn(),  
  )  
}
```

```

        params = sits_tuning_hparams(
            optimizer = choice(
                torchopt::optim_adamw,
                torchopt::optim_yogi
            ),
            opt_hparams = list(
                lr = beta(0.3, 5)
            )
        ),
        trials = 4,
        multicores = 2,
        progress = FALSE
    )
}

```

---

sits\_uncertainty

*Estimate classification uncertainty based on probs\_cube*


---

## Description

Calculate the uncertainty cube based on the probabilities produced by the classifier. Takes a probability cube as input. The uncertainty measure is relevant in the context of active learning, and helps to increase the quantity and quality of training samples by providing information about the confidence of the model. The supported types of uncertainty are 'entropy', 'least', and 'margin'. 'entropy' is the difference between all predictions expressed as entropy, 'least' is the difference between 100 prediction, and 'margin' is the difference between the two most confident predictions.

## Usage

```

sits_uncertainty(
  cube,
  ...,
  type = "entropy",
  multicores = 2L,
  memsize = 4L,
  output_dir,
  version = "v1"
)

## S3 method for class 'probs_cube'
sits_uncertainty(
  cube,
  ...,
  type = "entropy",
  multicores = 2,
  memsize = 4,
  output_dir,

```

```

    version = "v1"
  )

## S3 method for class 'probs_vector_cube'
sits_uncertainty(
  cube,
  ...,
  type = "entropy",
  multicores = 2,
  memsize = 4,
  output_dir,
  version = "v1"
)

## Default S3 method:
sits_uncertainty(cube, ..., type, multicores, memsize, output_dir, version)

```

### Arguments

cube	Probability data cube.
...	Other parameters for specific functions.
type	Method to measure uncertainty. See details.
multicores	Number of cores to run the function.
memsize	Maximum overall memory (in GB) to run the function.
output_dir	Output directory for image files.
version	Version of resulting image (in the case of multiple tests).

### Value

An uncertainty data cube

### Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Alber Sanchez, <alber.ipia@inpe.br>

### References

Monarch, Robert Munro. Human-in-the-Loop Machine Learning: Active learning and annotation for human-centered AI. Simon and Schuster, 2021.

### Examples

```

if (sits_run_examples()) {
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
}

```

```

# create a data cube from local files
data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
cube <- sits_cube(
  source = "BDC",
  collection = "MOD13Q1-6",
  data_dir = data_dir
)
# classify a data cube
probs_cube <- sits_classify(
  data = cube, ml_model = rfor_model, output_dir = tempdir()
)
# calculate uncertainty
uncert_cube <- sits_uncertainty(probs_cube, output_dir = tempdir())
# plot the resulting uncertainty cube
plot(uncert_cube)
}

```

---

sits\_uncertainty\_sampling

*Suggest samples for enhancing classification accuracy*

---

## Description

Suggest samples for regions of high uncertainty as predicted by the model. The function selects data points that have confused an algorithm. These points don't have labels and need be manually labelled by experts and then used to increase the classification's training set.

This function is best used in the following context: 1. Select an initial set of samples. 2. Train a machine learning model. 3. Build a data cube and classify it using the model. 4. Run a Bayesian smoothing in the resulting probability cube. 5. Create an uncertainty cube. 6. Perform uncertainty sampling.

The Bayesian smoothing procedure will reduce the classification outliers and thus increase the likelihood that the resulting pixels with high uncertainty have meaningful information.

## Usage

```

sits_uncertainty_sampling(
  uncert_cube,
  n = 100L,
  min_uncert = 0.4,
  sampling_window = 10L
)

```

## Arguments

uncert_cube	An uncertainty cube. See <a href="#">sits_uncertainty</a> .
n	Number of suggested points.
min_uncert	Minimum uncertainty value to select a sample.
sampling_window	Window size for collecting points (in pixels). The minimum window size is 10.

**Value**

A tibble with longitude and latitude in WGS84 with locations which have high uncertainty and meet the minimum distance criteria.

**Author(s)**

Alber Sanchez, <alber.ipia@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

Felipe Carvalho, <felipe.carvalho@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**References**

Robert Monarch, "Human-in-the-Loop Machine Learning: Active learning and annotation for human-centered AI". Manning Publications, 2021.

**Examples**

```
if (sits_run_examples()) {
  # create a data cube
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # build a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, ml_method = sits_rfor())
  # classify the cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # create an uncertainty cube
  uncert_cube <- sits_uncertainty(probs_cube,
    type = "entropy",
    output_dir = tempdir()
  )
  # obtain a new set of samples for active learning
  # the samples are located in uncertain places
  new_samples <- sits_uncertainty_sampling(
    uncert_cube,
    n = 10, min_uncert = 0.4
  )
}
```

---

sits_validate	<i>Validate time series samples</i>
---------------	-------------------------------------

---

### Description

One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set).

The function takes two arguments: a set of time series with a machine learning model and another set with validation samples. If the validation sample set is not provided, The sample dataset is split into two parts, as defined by the parameter `validation_split`. The accuracy is determined by the result of the validation test set.

This function returns the confusion matrix, and Kappa values.

### Usage

```
sits_validate(  
  samples,  
  samples_validation = NULL,  
  validation_split = 0.2,  
  ml_method = sits_rfor()  
)
```

### Arguments

<code>samples</code>	Time series to be validated (class "sits").
<code>samples_validation</code>	Optional: Time series used for validation (class "sits")
<code>validation_split</code>	Percent of original time series set to be used for validation if <code>samples_validation</code> is NULL (numeric value).
<code>ml_method</code>	Machine learning method (function)

### Value

A `caret::confusionMatrix` object to be used for validation assessment.

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  samples <- sits_sample(cerrado_2classes, frac = 0.5)
  samples_validation <- sits_sample(cerrado_2classes, frac = 0.5)
  conf_matrix_1 <- sits_validate(
    samples = samples,
    samples_validation = samples_validation,
    ml_method = sits_rfor()
  )
  conf_matrix_2 <- sits_validate(
    samples = cerrado_2classes,
    validation_split = 0.2,
    ml_method = sits_rfor()
  )
}

```

---

sits\_variance

*Calculate the variance of a probability cube*


---

**Description**

Takes a probability cube and estimate the local variance of the logit of the probability, to support the choice of parameters for Bayesian smoothing.

**Usage**

```

sits_variance(
  cube,
  window_size = 9L,
  neigh_fraction = 0.5,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## S3 method for class 'probs_cube'
sits_variance(
  cube,
  window_size = 9L,
  neigh_fraction = 0.5,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## S3 method for class 'raster_cube'

```



```

sits_variance(
  cube,
  window_size = 7L,
  neigh_fraction = 0.5,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## S3 method for class 'derived_cube'
sits_variance(
  cube,
  window_size = 7L,
  neigh_fraction = 0.5,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

## Default S3 method:
sits_variance(
  cube,
  window_size = 7L,
  neigh_fraction = 0.5,
  memsize = 4L,
  multicores = 2L,
  output_dir,
  version = "v1"
)

```

### Arguments

cube	Probability data cube (class "probs_cube")
window_size	Size of the neighborhood (odd integer)
neigh_fraction	Fraction of neighbors with highest probability for Bayesian inference (numeric from 0.0 to 1.0)
memsize	Maximum overall memory (in GB) to run the smoothing (integer, min = 1, max = 16384)
multicores	Number of cores to run the smoothing function (integer, min = 1, max = 2048)
output_dir	Output directory for image files (character vector of length 1)
version	Version of resulting image (character vector of length 1)

### Value

A variance data cube.

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

Rolf Simoes, <rolf.simoes@inpe.br>

**Examples**

```
if (sits_run_examples()) {
  # create a ResNet model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # plot the probability cube
  plot(probs_cube)
  # smooth the probability cube using Bayesian statistics
  var_cube <- sits_variance(probs_cube, output_dir = tempdir())
  # plot the variance cube
  plot(var_cube)
}
```

---

sits\_view

*View data cubes and samples in leaflet*


---

**Description**

Uses leaflet to visualize time series, raster cube and classified images

**Usage**

```
sits_view(x, ...)
```

## S3 method for class 'sits'

```
sits_view(x, ..., legend = NULL, palette = "Harmonic")
```

## S3 method for class 'data.frame'

```
sits_view(x, ..., legend = NULL, palette = "Harmonic")

## S3 method for class 'som_map'
sits_view(x, ..., id_neurons, legend = NULL, palette = "Harmonic")

## S3 method for class 'raster_cube'
sits_view(
  x,
  ...,
  band = NULL,
  red = NULL,
  green = NULL,
  blue = NULL,
  tiles = x[["tile"]],
  dates = NULL,
  class_cube = NULL,
  legend = NULL,
  palette = "RdYlGn",
  opacity = 0.7
)

## S3 method for class 'vector_cube'
sits_view(
  x,
  ...,
  band = NULL,
  red = NULL,
  green = NULL,
  blue = NULL,
  tiles = x[["tile"]],
  dates = NULL,
  class_cube = NULL,
  legend = NULL,
  palette = "RdYlGn",
  opacity = 0.7,
  seg_color = "black",
  line_width = 1
)

## S3 method for class 'uncertainty_cube'
sits_view(
  x,
  ...,
  tiles = x[["tile"]],
  class_cube = NULL,
  legend = NULL,
  palette = "Blues",
  opacity = 0.7
)
```

```

)

## S3 method for class 'class_cube'
sits_view(
  x,
  ...,
  tiles = x[["tile"]],
  legend = NULL,
  palette = "Spectral",
  opacity = 0.8
)

## S3 method for class 'probs_cube'
sits_view(
  x,
  ...,
  tiles = x[["tile"]],
  class_cube = NULL,
  legend = NULL,
  opacity = 0.7,
  palette = "YlGnBu"
)

## Default S3 method:
sits_view(x, ...)

```

### Arguments

x	Object of class "sits", "data.frame", "som_map", "raster_cube" or "classified image".
...	Further specifications for <a href="#">sits_view</a> .
legend	Named vector that associates labels to colors.
palette	Color palette (if colors not in legend nor in sits default colors)
id_neurons	Neurons from the SOM map to be shown.
band	For plotting grey images.
red	Band for red color.
green	Band for green color.
blue	Band for blue color.
tiles	Tiles to be plotted (in case of a multi-tile cube).
dates	Dates to be plotted.
class_cube	Classified cube to be overlayed on top on image.
opacity	Opacity of segment fill or class cube
seg_color	Color for segment boundaries
line_width	Line width for segments (in pixels)

**Value**

A leaflet object containing either samples or data cubes embedded in a global map that can be visualized directly in an RStudio viewer.

**Note**

Please refer to the sits documentation available in [<https://e-sensing.github.io/sitsbook/>](https://e-sensing.github.io/sitsbook/) for detailed examples.

**Author(s)**

Gilberto Camara, [<gilberto.camara@inpe.br>](mailto:gilberto.camara@inpe.br)

**Examples**

```
if (sits_run_examples()) {
  # view samples
  sits_view(cerrado_2classes)
  # create a local data cube
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  modis_cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # view the data cube
  sits_view(modis_cube,
    band = "NDVI"
  )
  # train a model
  rf_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify the cube
  modis_probs <- sits_classify(
    data = modis_cube,
    ml_model = rf_model,
    output_dir = tempdir()
  )
  # generate a map
  modis_label <- sits_label_classification(
    modis_probs,
    output_dir = tempdir()
  )
  # view the classified map
  sits_view(modis_label)
  # view the classified map with the B/W image
  sits_view(modis_cube,
    band = "NDVI",
    class_cube = modis_label,
    dates = sits_timeline(modis_cube)[[1]]
  )
  # view the classified map with the RGB image
  sits_view(modis_cube,
```

```
    red = "NDVI", green = "NDVI", blue = "NDVI",
    class_cube = modis_label,
    dates = sits_timeline(modis_cube)[[1]]
  )
  # create an uncertainty cube
  modis_uncert <- sits_uncertainty(
    cube = modis_probs,
    output_dir = tempdir()
  )
  # view the uncertainty cube
  sits_view(modis_uncert)
}
```

---

sits\_whittaker

*Filter time series with whittaker filter*

---

### Description

The algorithm searches for an optimal warping polynomial. The degree of smoothing depends on smoothing factor lambda (usually from 0.5 to 10.0). Use lambda = 0.5 for very slight smoothing and lambda = 5.0 for strong smoothing.

### Usage

```
sits_whittaker(data = NULL, lambda = 0.5)
```

### Arguments

data	Time series or matrix.
lambda	Smoothing factor to be applied (default 0.5).

### Value

Filtered time series

### Author(s)

Rolf Simoes, <rolf.simoese@inpe.br>  
Gilberto Camara, <gilberto.camara@inpe.br>  
Felipe Carvalho, <felipe.carvalho@inpe.br>

### References

Francesco Vuolo, Wai-Tim Ng, Clement Atzberger, "Smoothing and gap-filling of high resolution multi-spectral time series: Example of Landsat data", Int Journal of Applied Earth Observation and Geoinformation, vol. 57, pg. 202-213, 2107.

**See Also**[sits\\_apply](#)**Examples**

```
if (sits_run_examples()) {  
  # Retrieve a time series with values of NDVI  
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")  
  # Filter the point using the Whittaker smoother  
  point_whit <- sits_filter(point_ndvi, sits_whittaker(lambda = 3.0))  
  # Merge time series  
  point_ndvi <- sits_merge(point_ndvi, point_whit,  
                           suffix = c("", ".WHIT"))  
  # Plot the two points to see the smoothing effect  
  plot(point_ndvi)  
}
```

---

**sits\_xgboost***Train extreme gradient boosting models*

---

**Description**

This function uses the extreme gradient boosting algorithm. Boosting iteratively adds basis functions in a greedy fashion so that each new basis function further reduces the selected loss function. This function is a front-end to the methods in the "xgboost" package. Please refer to the documentation in that package for more details.

**Usage**

```
sits_xgboost(  
  samples = NULL,  
  learning_rate = 0.15,  
  min_split_loss = 1,  
  max_depth = 5,  
  min_child_weight = 1,  
  max_delta_step = 1,  
  subsample = 0.8,  
  nfold = 5,  
  nrounds = 100,  
  nthread = 6,  
  early_stopping_rounds = 20,  
  verbose = FALSE  
)
```

**Arguments**

samples	Time series with the training samples.
learning_rate	Learning rate: scale the contribution of each tree by a factor of $0 < lr < 1$ when it is added to the current approximation. Used to prevent overfitting. Default: 0.15
min_split_loss	Minimum loss reduction to make a further partition of a leaf. Default: 1.
max_depth	Maximum depth of a tree. Increasing this value makes the model more complex and more likely to overfit. Default: 5.
min_child_weight	If the leaf node has a minimum sum of instance weights lower than min_child_weight, tree splitting stops. The larger min_child_weight is, the more conservative the algorithm is. Default: 1.
max_delta_step	Maximum delta step we allow each leaf output to be. If the value is set to 0, there is no constraint. If it is set to a positive value, it can help making the update step more conservative. Default: 1.
subsample	Percentage of samples supplied to a tree. Default: 0.8.
nfold	Number of the subsamples for the cross-validation.
nrounds	Number of rounds to iterate the cross-validation (default: 100)
nthread	Number of threads (default = 6)
early_stopping_rounds	Training with a validation set will stop if the performance doesn't improve for k rounds.
verbose	Print information on statistics during the process

**Value**

Model fitted to input data (to be passed to [sits\\_classify](#))

**Note**

Please refer to the sits documentation available in <https://e-sensing.github.io/sitsbook/> for detailed examples.

**Author(s)**

Rolf Simoes, <rolf.simoes@inpe.br>

Gilberto Camara, <gilberto.camara@inpe.br>

**References**

Tianqi Chen, Carlos Guestrin, "XGBoost : Reliable Large-scale Tree Boosting System", SIG KDD 2016.



**Examples**

```

if (sits_run_examples()) {
  # Example of training a model for time series classification
  # Retrieve the samples for Mato Grosso
  # train a xgboost model
  ml_model <- sits_train(samples_modis_ndvi, ml_method = sits_xgboost)
  # classify the point
  point_ndvi <- sits_select(point_mt_6bands, bands = "NDVI")
  # classify the point
  point_class <- sits_classify(
    data = point_ndvi, ml_model = ml_model
  )
  plot(point_class)
}

```

---

summary.class\_cube      *Summarize data cubes*

---

**Description**

This is a generic function. Parameters depend on the specific type of input.

**Usage**

```

## S3 method for class 'class_cube'
summary(object, ..., tile = NULL)

```

**Arguments**

object	Object of class "class_cube"
...	Further specifications for <a href="#">summary</a> .
tile	Tile to be summarized

**Value**

A summary of a classified cube

**Author(s)**

Gilberto Camara, <gilberto.camara@inpe.br>

**Examples**

```

if (sits_run_examples()) {
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",

```

```
        collection = "MOD13Q1-6",
        data_dir = data_dir
    )
    # create a random forest model
    rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
    # classify a data cube
    probs_cube <- sits_classify(
        data = cube, ml_model = rfor_model, output_dir = tempdir()
    )
    # label the probability cube
    label_cube <- sits_label_classification(
        probs_cube,
        output_dir = tempdir()
    )
    summary(label_cube)
}
```

---

summary.raster\_cube    *Summarize data cubes*

---

## Description

This is a generic function. Parameters depend on the specific type of input.

## Usage

```
## S3 method for class 'raster_cube'
summary(object, ..., tile = NULL, date = NULL)
```

## Arguments

object	Object of classes "raster_cube".
...	Further specifications for <a href="#">summary</a> .
tile	Tile to be summarized
date	Date to be summarized

## Value

A summary of the data cube.

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>  
Felipe Souza, <felipe.souza@inpe.br>

## Examples

```
if (sits_run_examples()) {  
  # create a data cube from local files  
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")  
  cube <- sits_cube(  
    source = "BDC",  
    collection = "MOD13Q1-6",  
    data_dir = data_dir  
  )  
  summary(cube)  
}
```

---

summary.sits

*Summarize sits*

---

## Description

This is a generic function. Parameters depend on the specific type of input.

## Usage

```
## S3 method for class 'sits'  
summary(object, ...)
```

## Arguments

object            Object of classes "sits".  
...                Further specifications for [summary](#).

## Value

A summary of the sits tibble.

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

Felipe Souza, <felipe.souza@inpe.br>

## Examples

```
if (sits_run_examples()) {  
  summary(samples_modis_ndvi)  
}
```

---

summary.sits\_accuracy *Summarize accuracy matrix for training data*

---

## Description

This is a generic function. Parameters depend on the specific type of input.

## Usage

```
## S3 method for class 'sits_accuracy'  
summary(object, ...)
```

## Arguments

object            Object of classe "sits\_accuracy".  
...               Further specifications for [summary](#).

## Value

A summary of the sample accuracy

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```
if (sits_run_examples()) {  
  data(cerrado_2classes)  
  # split training and test data  
  train_data <- sits_sample(cerrado_2classes, frac = 0.5)  
  test_data <- sits_sample(cerrado_2classes, frac = 0.5)  
  # train a random forest model  
  rfor_model <- sits_train(train_data, sits_rfor())  
  # classify test data  
  points_class <- sits_classify(  
    data = test_data,  
    ml_model = rfor_model  
  )  
  # measure accuracy  
  acc <- sits_accuracy(points_class)  
  summary(acc)  
}
```

---

```
summary.sits_area_accuracy
      Summarize accuracy matrix for area data
```

---

## Description

This is a generic function. Parameters depend on the specific type of input.

## Usage

```
## S3 method for class 'sits_area_accuracy'
summary(object, ...)
```

## Arguments

object	Object of classe "sits_accuracy".
...	Further specifications for <a href="#">summary</a> .

## Value

A summary of the sample accuracy

## Author(s)

Gilberto Camara, <gilberto.camara@inpe.br>

## Examples

```
if (sits_run_examples()) {
  # create a data cube from local files
  data_dir <- system.file("extdata/raster/mod13q1", package = "sits")
  cube <- sits_cube(
    source = "BDC",
    collection = "MOD13Q1-6",
    data_dir = data_dir
  )
  # create a random forest model
  rfor_model <- sits_train(samples_modis_ndvi, sits_rfor())
  # classify a data cube
  probs_cube <- sits_classify(
    data = cube, ml_model = rfor_model, output_dir = tempdir()
  )
  # label the probability cube
  label_cube <- sits_label_classification(
    probs_cube,
    output_dir = tempdir()
  )
  # obtain the ground truth for accuracy assessment
  ground_truth <- system.file("extdata/samples/samples_sinop_crop.csv",
```

```

    package = "sits"
  )
  # make accuracy assessment
  as <- sits_accuracy(label_cube, validation = ground_truth)
  summary(as)
}

```

---

'sits\_labels<-'      *Change the labels of a set of time series*

---

### Description

Given a sits tibble with a set of labels, renames the labels to the specified in value.

### Usage

```

sits_labels(data) <- value

## S3 replacement method for class 'sits'
sits_labels(data) <- value

## S3 replacement method for class 'probs_cube'
sits_labels(data) <- value

## S3 replacement method for class 'class_cube'
sits_labels(data) <- value

## Default S3 replacement method:
sits_labels(data) <- value

```

### Arguments

data	Data cube or time series.
value	A character vector used to convert labels. Labels will be renamed to the respective value positioned at the labels order returned by <a href="#">sits_labels</a> .

### Value

A sits tibble or data cube with modified labels.  
 A probs or class\_cube cube with modified labels.

### Author(s)

Rolf Simoes, <rolf.simoes@inpe.br>

'sits\_labels<-'

167

### Examples

```
# show original samples ("Cerrado" and "Pasture")
sits_labels(cerrado_2classes)
# rename label samples to "Savanna" and "Grasslands"
sits_labels(cerrado_2classes) <- c("Savanna", "Grasslands")
# see the change
sits_labels(cerrado_2classes)
```

# Index

- \* **datasets**
  - cerrado\_2classes, 7
  - point\_mt\_6bands, 32
  - samples\_l8\_rondonia\_2bands, 32
  - samples\_modis\_ndvi, 33
- 'sits\_labels<-', 166
- cerrado\_2classes, 7
- impute\_linear, 7
- kohonen::supersom, 128
- plot, 8, 8, 9, 11–15, 17–25, 27, 28, 30, 31, 119
- plot.class\_cube, 8, 9
- plot.class\_vector\_cube, 8, 10
- plot.geo\_distances, 12
- plot.patterns, 8, 13
- plot.predicted, 8, 14
- plot.probs\_cube, 8, 15
- plot.probs\_vector\_cube, 16
- plot.raster\_cube, 8, 18
- plot.rfor\_model, 8, 19
- plot.sits, 8
- plot.sits\_accuracy, 20
- plot.sits\_cluster, 21
- plot.som\_evaluate\_cluster, 8, 22
- plot.som\_map, 8, 23
- plot.torch\_model, 8, 24
- plot.uncertainty\_cube, 8, 25
- plot.uncertainty\_vector\_cube, 26
- plot.variance\_cube, 28
- plot.vector\_cube, 8, 29
- plot.xgb\_model, 8, 31
- point\_mt\_6bands, 32
- samples\_l8\_rondonia\_2bands, 32
- samples\_modis\_ndvi, 33
- sits (sits-package), 6
- sits-package, 6
- sits\_accuracy, 33, 142
- sits\_apply, 35, 159
- sits\_as\_sf, 38
- sits\_bands, 39
- sits\_bands<- (sits\_bands), 39
- sits\_bbox, 41
- sits\_classify, 33, 42, 59, 114, 119, 134, 143, 160
- sits\_clean, 46
- sits\_cluster\_clean, 48
- sits\_cluster\_dendro, 49
- sits\_cluster\_frequency, 51
- sits\_colors, 52
- sits\_colors\_qgis, 53
- sits\_colors\_reset, 54
- sits\_colors\_set, 54
- sits\_colors\_show, 55
- sits\_combine\_predictions, 56
- sits\_confidence\_sampling, 58
- sits\_config, 60
- sits\_config\_show, 61
- sits\_cube, 61, 118, 125
- sits\_cube\_copy, 67
- sits\_factory\_function, 69
- sits\_filter, 70
- sits\_formula\_linear, 71
- sits\_formula\_logref, 72
- sits\_geo\_dist, 73
- sits\_get\_data, 74
- sits\_impute, 78
- sits\_kfold\_validate, 79
- sits\_label\_classification, 33, 83, 119
- sits\_labels, 80, 166
- sits\_labels<- ('sits\_labels<-'), 166
- sits\_labels\_summary, 82
- sits\_lighttae, 42, 85, 143
- sits\_list\_collections, 63, 87
- sits\_merge, 88
- sits\_mgrs\_to\_roi, 89
- sits\_mixture\_model, 90



sits\_mlp, [42](#), [92](#), [143](#)  
sits\_model\_export, [95](#)  
sits\_mosaic, [95](#)  
sits\_patterns, [97](#)  
sits\_pred\_features, [99](#)  
sits\_pred\_normalize, [100](#)  
sits\_pred\_reference, [101](#)  
sits\_pred\_references  
    (sits\_pred\_reference), [101](#)  
sits\_pred\_sample, [101](#)  
sits\_predictors, [98](#)  
sits\_reclassify, [102](#)  
sits\_reduce, [105](#)  
sits\_reduce\_imbalance, [107](#)  
sits\_regularize, [109](#), [118](#)  
sits\_resnet, [42](#), [111](#), [143](#)  
sits\_rfor, [42](#), [114](#), [143](#)  
sits\_run\_examples, [115](#)  
sits\_run\_tests, [116](#)  
sits\_sample, [116](#)  
sits\_sampling\_design, [117](#)  
sits\_segment, [44](#), [118](#), [118](#)  
sits\_select, [120](#)  
sits\_sgolay, [44](#), [122](#)  
sits\_slic, [123](#)  
sits\_smooth, [59](#), [125](#)  
sits\_som, [127](#)  
sits\_som\_clean\_samples, [129](#)  
sits\_som\_evaluate\_cluster, [130](#)  
sits\_som\_map, [130](#)  
sits\_som\_map(sits\_som), [127](#)  
sits\_stats, [131](#)  
sits\_stratified\_sampling, [132](#)  
sits\_svm, [42](#), [133](#), [143](#)  
sits\_tae, [135](#)  
sits\_tempcnn, [42](#), [137](#), [143](#)  
sits\_timeline, [140](#)  
sits\_to\_csv, [141](#)  
sits\_to\_xlsx, [142](#)  
sits\_train, [42](#), [43](#), [143](#)  
sits\_tuning, [144](#)  
sits\_tuning\_hparams, [146](#)  
sits\_uncertainty, [147](#), [149](#)  
sits\_uncertainty\_sampling, [149](#)  
sits\_validate, [151](#)  
sits\_variance, [152](#)  
sits\_view, [119](#), [154](#), [156](#)  
sits\_whittaker, [44](#), [158](#)  
sits\_xgboost, [42](#), [143](#), [159](#)  
summary, [161–165](#)  
summary.class\_cube, [161](#)  
summary.raster\_cube, [162](#)  
summary.sits, [163](#)  
summary.sits\_accuracy, [164](#)  
summary.sits\_area\_accuracy, [165](#)