
HUB-Datacube Documentation

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User Guides:

1	Setting up	3
2	Example	5
	Python Module Index	21

The HUB-Datacube (HUBDC) offers a high level interface for integrating heterogeneous raster and vector datasets into a user-defined reference pixel grid, resulting in an analysis-ready datacube.

Please provide feedback to [Andreas Rabe](mailto:Andreas.Rabe@geo.hu-berlin.de) (andreas.rabe@geo.hu-berlin.de), or open an issue on [Bitbucket](#).

CHAPTER 1

Setting up

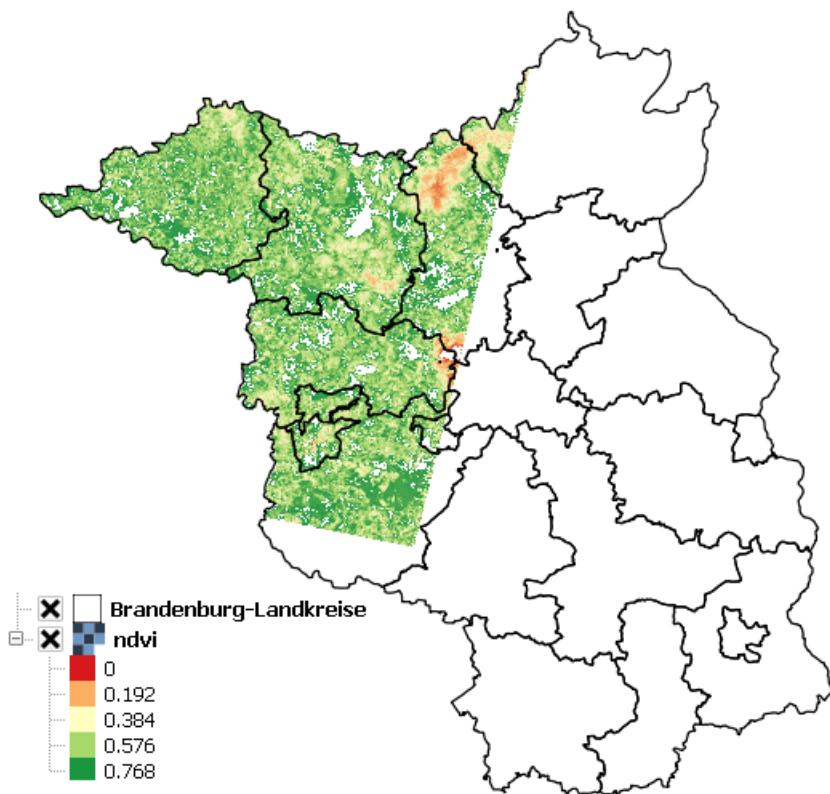
Install the latest release with pip:

```
python -m pip install https://bitbucket.org/hu-geomatics/hub-datacube/get/master.tar.  
→gz
```

Or manually download a [release](#) from Bitbucket.

CHAPTER 2

Example



"""

Calculate the Normalized Difference Vegetation Index (NDVI) for a Landsat 5 scene.
Mask the resulting image to the shape of Brandenburg (a federated state of Germany).

"""

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```

import tempfile
import os
import numpy
from hubdc.applier import *
from hubdctestdata import LT51940232010189KIS01, BrandenburgDistricts

# Set up input and output filenames.
applier = Applier()
applier.inputRaster.setRaster(key='red',
    ↪value=ApplierInputRaster(filename=LT51940232010189KIS01.red))
applier.inputRaster.setRaster(key='nir',
    ↪value=ApplierInputRaster(filename=LT51940232010189KIS01.nir))
applier.inputVector.setVector(key='brandenburg',
    ↪value=ApplierInputVector(filename=BrandenburgDistricts.shp))
applier.outputRaster.setRaster(key='ndvi', value=ApplierOutputRaster(filename=os.path.
    ↪join(tempfile.gettempdir(), 'ndvi.img')))

# Set up the operator to be applied
class NDVIOperator(ApplierOperator):
    def ufunc(operator):

        # read image data
        red = operator.inputRaster.raster(key='red').array()
        nir = operator.inputRaster.raster(key='nir').array()
        brandenburg = operator.inputVector.vector(key='brandenburg').
            ↪array(initValue=0, burnValue=1)

        # calculate ndvi and mask Brandenburg
        ndvi = numpy.float32(nir-red)/(nir+red)
        ndvi[brandenburg==0] = -1

        # write ndvi data
        operator.outputRaster.raster(key='ndvi').setArray(array=ndvi)

    # Apply the operator to the inputs, creating the outputs.
    applier.apply(operatorType=NDVIOperator)
    print(applier.outputRaster.raster(key='ndvi').filename)

    # Python prints something like:
    # >>> c:\users\USER\appdata\local\temp\ndvi.img

```

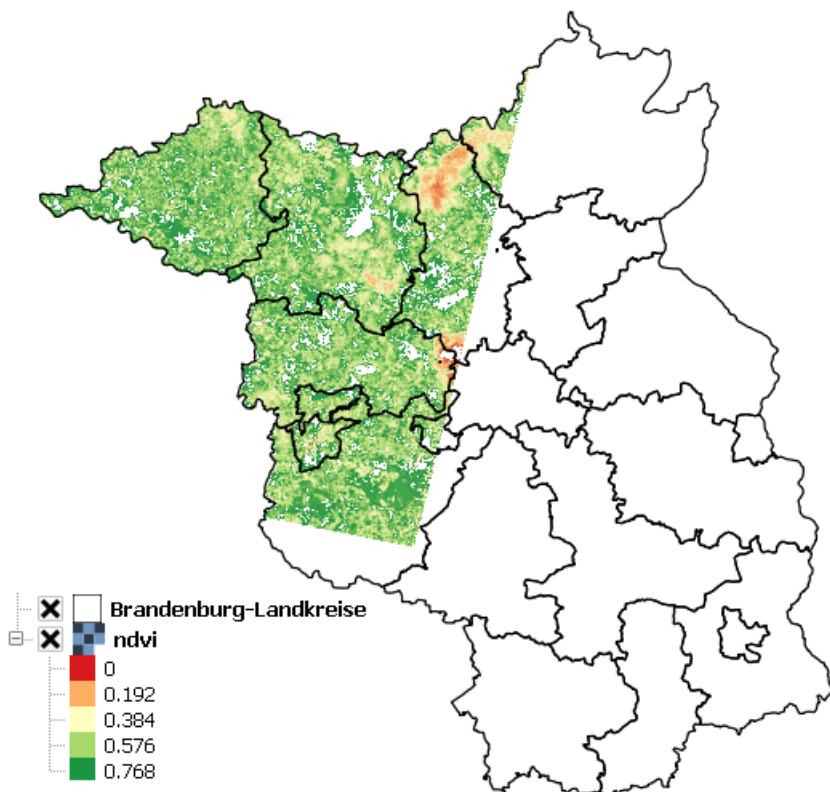
See *Applier Examples* for more information.

2.1 Applier Examples

To honor the similarities of HUBDC with RIOS, we replicate the examples known from RIOS, and add some more HUBDC specific examples.

2.1.1 Simple Example (explained in detail)

Use the Red and NIR bands of the Landsat `LT51940232010189KIS01` scene to calculate the Normalized Difference Vegetation Index (NDVI). Additionally, use the `BrandenburgDistricts` vector polygon layer to mask the result.



```
"""
Calculate Normalized Difference Vegetation Index (NDVI) for a Landsat 5 scene and cut
the result to the German state Brandenburg.
"""

import tempfile
import os
import numpy
from hubdc.applier import *
from hubdctestdata import LT51940232010189KIS01, BrandenburgDistricts

# Set up input and output filenames.
applier = Applier()
applier.inputRaster.setRaster(key='red',
    value=ApplierInputRaster(filename=LT51940232010189KIS01.red))
applier.inputRaster.setRaster(key='nir',
    value=ApplierInputRaster(filename=LT51940232010189KIS01.nir))
applier.inputVector.setVector(key='brandenburg',
    value=ApplierInputVector(filename=BrandenburgDistricts.shp))
applier.outputRaster.setRaster(key='ndvi', value=ApplierOutputRaster(filename=os.path.
    join(tempfile.gettempdir(), 'ndvi.img')))

# Set up the operator to be applied
class NDVIOperator(ApplierOperator):
    def ufunc(operator):

        # read image data
        red = operator.inputRaster.raster(key='red').imageArray()
        nir = operator.inputRaster.raster(key='nir').imageArray()
```

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```

brandenburg = operator.inputVector.vector(key='brandenburg') .
˓→imageArray(initValue=0, burnValue=1)

# calculate ndvi and mask Brandenburg
ndvi = numpy.float32(nir-red) / (nir+red)
ndvi[brandenburg==0] = -1

# write ndvi data
operator.outputRaster.raster(key='ndvi').setImageArray(array=ndvi)

# Apply the operator to the inputs, creating the outputs.
applier.apply(operatorType=NDVIOperator)
print(applier.outputRaster.raster(key='ndvi').filename)

```

The result is stored in the file called `ndvi.img` stored in the user `tempdir` (e.g. on Windows systems `c:\users\USER\appdata\local\temp\ndvi.img`).

HUB-Datacube Applier programs are usually structured in the following way:

1. Initialize the Applier

```
applier = Applier()
```

2. Assigning raster inputs ...

```

applier.inputRaster.setRaster(key='image1',
˓→value=ApplierInputRaster(filename=LT51940232010189KIS01.swirl1))
applier.inputRaster.setRaster(key='image2',
˓→value=ApplierInputRaster(filename=LT51940232010189KIS01.swirl2))

```

... vector inputs ...

```
applier.inputVector.setVector(key='brandenburg',
˓→value=ApplierInputVector(filename=BrandenburgDistricts.shp))
```

... and raster outputs

```

applier.outputRaster.setRaster(key='outimage',
˓→value=ApplierOutputRaster(filename=os.path.join(tempfile.gettempdir(),
˓→'outimage.img')))
```

Note that all input and output datasets are set using different members of the `applier` object:

`applier.inputRaster` is an `ApplierInputRasterGroup` object, which is a container for `ApplierInputRaster` objects

`applier.inputVector` is an `ApplierInputVectorGroup` object, which is a container for `ApplierInputVector` objects

`applier.outputRaster` is an `ApplierOutputRasterGroup` object, which is a container for `ApplierOutputRaster` objects

3. Implement an operator class derived from `ApplierOperator` and overwriting the `ufunc` method

```

class NDVIOperator(ApplierOperator):
    def ufunc(operator):
        ...

```

The `ufunc` method is usually structured into the sections:

(a) read data into numpy arrays

```
# read image data
red = operator.inputRaster.raster(key='red').imageArray()
nir = operator.inputRaster.raster(key='nir').imageArray()
brandenburg = operator.inputVector.vector(key='brandenburg').
    ↪imageArray(initValue=0, burnValue=1, dtype=numpy.uint8)
```

Note that all input datasets are access using different members of the `operator` object:

`operator.inputRaster` is identical to `applier.inputRaster` and used to access previously defined `ApplierInputRaster` objects, which can be used to read raster data, see `imageArray()`

`operator.inputVector` is identical to `applier.inputVector` and is used to access previously defined `ApplierInputVector` objects, which can be used to read and rasterize vector data, see `imageArray()`

Also note that input data is presented as numpy arrays, of the datatype corresponding to that in the raster files. It is the responsibility of the user to manage all conversions of datatypes.

All blocks of data are 3-d numpy arrays. The first dimension corresponds to the number of layers in the image file, and will be present even when there is only one layer. The second and third dimensions represent the spatial extent (ysize, xsize) of the image block.

(b) data processing

```
# calculate ndvi and mask Brandenburg
ndvi = numpy.float32(nir-red) / (nir+red)
ndvi[brandenburg==0] = -1
```

(c) write output data (and metadata - not shown here)

```
# write ndvi data
operator.outputRaster.raster(key='ndvi').setImageArray(array=ndvi)
```

Note that output raster datasets are access using the `operator.outputRaster`, which is identical to `applier.outputRaster` and used to access previously defined `ApplierOutputRaster` objects, which can be used to write output numpy arrays, see `setImageArray()`.

The datatype of the output files will be inferred from the datatype of the given numpy arrays. So, to control the datatype of the output file, use for example the `numpy.astype` function to control the datatype of the output arrays.

2.1.2 Manage Metadata Example

You can read metadata from input and write metadata to output datasets

This simple example reads the *wavelength* information from the *ENVI* metadata domain of an input dataset and passes it to an output dataset:

```
def ufunc(operator):
    # copy raster data
    array = operator.inputRaster.raster(key='image').imageArray()
    operator.outputRaster.raster(key='outimage').setImageArray(array)
```

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```
# copy ENVI/wavelength metadata
wavelength = operator.inputRaster.raster(key='image').metadataItem(key='wavelength',
→, domain='ENVI')
operator.outputRaster.raster(key='outimage').setMetadataItem(key='wavelength',
→value=wavelength, domain='ENVI')
```

See `metadataItem()` and `setMetadataItem()` for more details.

For more information on the GDAL Data and Metadata Model see the [GDAL documentation](#).

For more information on the ENVI Metadata Model see [The ENVI Header Format](#)

2.1.3 Passing Other Data Example

Use additional arguments for passing other data into the operator user function, apart from the raster data itself. This is obviously useful for passing parameters into the processing.

Use the `return` statement to pass information out again.

A simple example, using it to pass in a single parameter, might be a program to multiply an input raster by a scale value and add an offset:

```
class ScaleOperator(ApplierOperator):
    def ufunc(operator, scale, offset):
        array = operator.inputRaster.raster(key='image').imageArray()
        scaled = array * scale + offset
        operator.outputRaster.raster(key='outimage').setImageArray(array=scaled)

applier.apply(operatorType=Scaleoperator, scale=1, offset=0)
```

An example of using the `return` statement to accumulate information across blocks might be a program to calculate some statistic (e.g. the mean) across the whole raster:

```
class MeanOperator(ApplierOperator):
    def ufunc(operator):
        array = operator.inputRaster.raster(key='image').imageArray()
        blockTotal = img.sum()
        blockCount = img.size
        return blockTotal, blockCount

results = applier.apply(operatorType=MeanOperator)

total, count = 0., 0
for blockTotal, blockCount in results:
    total += blockTotal
    count += blockCount

print('Average value = ', total / count)
```

The `total` and `count` values are calculated from the list of `blockTotal` and `blockCount` values returned by the `apply()` method.

The values could be accumulated between blocks, as looping sequentially over all blocks in the image, but this approach would fail if the applier is used with multiprocessing enabled.

Of course, there already exist superior ways of calculating the mean value of an image, but the point about using the applier to do something like this would be that: a) opening the input rasters is taken care of; and b) it takes up very little

memory, as only small blocks are in memory at one time. The same mechanism can be used to do more specialized calculations across the images.

Note that there are no output rasters from the last example - this is perfectly valid.

2.1.4 Controlling the Reference Pixel Grid Example

Use `setProjection()`, `setResolution()`, and `setExtent()` to explicitly control the grid projection, resolution and extent:

```
applier.controls.setProjection(projection=Projection('PROJCS["UTM_Zone_33N",GEOGCS[  
    "GCS_WGS_1984",DATUM["WGS_1984",SPHEROID["WGS_84",6378137.0,298.257223563]],PRIMEM[  
    "Greenwich",0.0],UNIT["Degree",0.0174532925199433]],PROJECTION["Transverse_Mercator  
    "],PARAMETER["False_Easting",500000.0],PARAMETER["False_Northing",0.0],PARAMETER[  
    "Central_Meridian",15.0],PARAMETER["Scale_Factor",0.9996],PARAMETER["Latitude_Of_  
    Origin",0.0],UNIT["Meter",1]]'))  
applier.controls.setExtent(extent=Extent(xmin=4400000, xmax=4500000, ymin=3100000,  
    ymax=3200000)  
applier.controls.setResolution(resolution=x=30, y=30)
```

2.1.5 Other Controls

Other controls which can be manipulated are detailed in the `ApplierControls` class.

2.1.6 Arbitrary Numbers of Input (and Output) Files Example

As mentioned before, the `applier` members `applier.inputRaster`, `applier.inputVector` and `applier.outputRaster` are container objects of type `ApplierInputRasterGroup`, `ApplierInputVectorGroup` and `ApplierOutputRasterGroup` respectively.

These containers are used to store `ApplierInputRaster`, `ApplierInputVector` and `ApplierOutputRaster` objects respectively.

Furthermore, a container can store other containers of the same type, which enables the creation of more complex, nested dataset structures. This makes it possible to represent naming structures comparable to those on the users file system.

An example: given a small Landsat archive of 8 scenes in 4 footprints stored on the file system structured by path/row/scene. Let assume, we are only interested in the CFMask datasets:

```
C:\landsat\  
    194\  
        023\  
            LC81940232015235LGN00\  
                LC81940232015235LGN00_cfmask.img  
                ...  
            LE71940232015275NSG00\  
                LE71940232015275NSG00_cfmask.img  
                ...  
            LT41940231990126XXX05\  
                LT41940231990126XXX05_cfmask.img  
                ...  
            LT51940232010189KIS01\  
                LT51940232010189KIS01_cfmask.img
```

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```

194\
    ...
024\
    LC81940242015235LGN00\
        LC81940242015235LGN00_cfmask.img
        ...
LE71940242015275NSG00\
    LE71940242015275NSG00_cfmask.img
    ...
LT41940241990126XXX03\
    LT41940241990126XXX03_cfmask.img
    ...
LT51940242010189KIS01\
    LT51940242010189KIS01_cfmask.img
    ...

```

The CFMask datasets can be inserted manually (preserving the file structure) as follows:

```

landsat = applier.inputRaster.setGroup('landsat', value=ApplierInputRasterGroup())
path194 = landsat.setGroup('194', value=ApplierInputRasterGroup())
row023 = path194.setGroup(key='023', value=ApplierInputRasterGroup())
row024 = path194.setGroup(key='024', value=ApplierInputRasterGroup())

row023.setRaster(key='LC81940232015235LGN00_cfmask', ↴
    ↪value=ApplierInputRaster(filename=r
    ↪'C:\landsat\194\023\LC81940232015235LGN00\LC81940232015235LGN00_cfmask.img'))
...
row024.setRaster(key='LT51940242010189KIS01_cfmask', ↴
    ↪value=ApplierInputRaster(filename=r
    ↪'C:\landsat\194\023\LT51940242010189KIS01\LT51940242010189KIS01_cfmask.img'))
```

The same result can be achieved using the `fromFolder()` auxilliary method, which takes a `folder` and searches recursively for all raster matching the given `extensions` and passes a (optional) `ufunc` filter function:

```

ufunc = lambda root, basename, extension: basename.endswith('cfmask')
applier.inputRaster.setGroup(key='landsat', value=ApplierInputRasterGroup.
    ↪fromFolder(folder=r'C:\Work\data\gms\landsat',
    ↪extensions=['.img'],
    ↪ufunc=ufunc)
```

Inside the operator `ufunc`, individual datasets can then be accessed as follows:

```

def ufunc(operator):
    # access individual dataset
    cfmask = operator.inputRaster.group(key='landsat').group(key='194').group(key='023'
    ↪).group(key='LC81940232015235LGN00').raster(key='LC81940232015235LGN00_cfmask')
    array = cfmask.imageArray()
```

Or as a shortcut to this it is possible to also use key concatenation like so:

```

cfmask = operator.inputRaster.raster(key='landsat/194/023/LC81940232015235LGN00/
    ↪LC81940232015235LGN00_cfmask')
```

To visit all datasets, the structure can be iterated in accordance to how it was created, from landsat, over pathes, over rows, over scenes, to the cfmask rasters:

```
def ufunc(operator):
    # iterate over all datasets
    landsat = operator.inputRaster.group(key='landsat')
    for path in landsat.groups():
        for row in path.groups():
            for scene in row.groups():
                cfmask = scene.findRaster(ufunc=lambda key, raster: key.endswith(
                    'cfmask'))
                array = cfmask.imageArray()
```

The rasters can also be flat iterated, ignoring the group structure completely:

```
def ufunc(operator):
    # flat iterate over all datasets
    for cfmask in operator.inputRaster.flatRasters():
        array = cfmask.imageArray()
```

2.1.7 Filters and Overlap Example

Because the applier operates on a per block basis, care must be taken to set the overlap correctly when working with filters. The `overlap` keyword must be consistently set when using input raster reading methods (`imageArray()`, `bandArray()`, `fractionArray()`), input vector reading methods (`imageArray()` `fractionArray()`), and output raster writing method (`setImageArray()`).

Here is a simple convolution filter example:

```
import tempfile
import os
from scipy.ndimage import uniform_filter

from hubdc.applier import *
from hubdc.testdata import LT51940232010189KIS01

applier = Applier()
applier.inputRaster.setRaster(key='image',
    ↪value=ApplierInputRaster(filename=LT51940232010189KIS01.band3))
applier.outputRaster.setRaster(key='outimage', value=ApplierOutputRaster(filename=os.
    ↪path.join(tempfile.gettempdir(), 'smoothed.img')))

class SmoothOperator(ApplierOperator):
    def ufunc(operator):

        # does a spatial 11x11 uniform filter.
        # Note: for a 3x3 the overlap is 1, 5x5 overlap is 2, ..., 11x11 overlap is 5,
        ↪etc
        overlap = 5
        array = operator.inputRaster.raster(key='image').imageArray(overlap=overlap)
        arraySmoothed = uniform_filter(array, size=11, mode='constant')
        operator.outputRaster.raster(key='outimage').
            ↪setImageArray(array=arraySmoothed, overlap=overlap)

applier.apply(operatorType=SmoothOperator)
```

Many other Scipy filters are also available and can be used in a similar way.

2.1.8 Categorical Raster Inputs Example

On-the-fly resampling and reprojection of input rasters into the reference pixel grid is one key feature of the applier. However, for categorical raster inputs, this default behaviour can be insufficient in terms of information content preservation, even if the resampling algorithm is carefully chosen.

For example, if the goal is to process a categorical raster, where different categories are coded with unique ids, standard resampling algorithms will not be able to preserve the information content.

Sometimes it is sufficient to use the gdal.GRA_Mode algorithms, but in general it is not. To resample a categorical raster into a target pixel grid with a different resolution usually implies that the categorical information must be aggregated into pixel fraction, one for each category.

In the following example a Landsat CFMask image at 30 m is resampled into 250 m, resulting in a category fractions. The categories are: 0 is *clear land*, 1 is *clear water*, 2 is *cloud shadow*, 3 is *ice or snow*, 4 is *cloud* and 255 is the *background*. Use `fractionArray()` to achieve this:

```
cfmaskFractions250m = self.inputRaster.raster('cfmask30m').  
    ↪fractionArray(categories=[0, 1, 2, 3, 4, 255])
```

Categories at 250 m can then be calculated from the aggregated fractions:

```
cfmask250m = numpy.array([0, 1, 2, 4, 255])[cfmaskFractions250m.argmax(axis=0)]
```

2.1.9 Vector Inputs Example

Vector layers can be included into the processing:

```
applier = Applier()  
applier.inputVector.setVector(key='vector',  
    ↪value=ApplierInputVector(filename=myShapefile))
```

Like any input raster file, vector layers can be accessed via the `operator` object inside the user function:

```
def ufunc(operator):  
    vector = operator.inputVector.vector(key='vector')
```

Use `imageArray()` to get a rasterized version of the vector layer. The rasterization is a binary mask by default, that is initialized with 0 and all pixels covered by features are filled (burned) with a value of 1:

```
array = vector.imageArray()
```

This behaviour can be altered using the `initValue` and `burnValue` keywords:

```
array = vector.imageArray(initValue=0, burnValue=1)
```

Instead of a constant burn value, a burn attribute can be set by using the `burnAttribute` keyword:

```
array = vector.imageArray(burnAttribute='ID')
```

Use the `filterSQL` keyword to set an attribute query string in form of a SQL WHERE clause. Only features for which the query evaluates as true will be returned:

```
sqlWhere = "Name = 'Vegetation'"  
array = vector.imageArray(filterSQL=sqlWhere)
```

2.1.10 Categorical Vector Inputs Example

In some situations it may be insufficient to simply burn a value or attribute value (i.e. categories) onto the target reference pixel grid. Depending on the detailedness of the vector shapes (i.e. scale of digitization), a simple burn or not burn decision may greatly degrade the information content if the target resolution (i.e. scale of rasterization) is much coarser.

In this case it would be desirable to rasterize the categories at the scale of digitization and afterwards aggregate this categorical information into pixel fraction, one for each category.

Take for example a vector layer with an attribute CLASS_ID coding features as 1 -> *Impervious*, 2 -> *Vegetation*, 3 -> *Soil* and 4 -> *Other*. To derive aggregated pixel fractions for *Impervious*, *Vegetation* and *Soil* categories rasterization at 5 m resolution use `fractionArray()`:

```
def ufunc(operator):
    vector = operator.inputVector.vector(key='vector')
    fractions = self.fractionArray('vector', categories=[1, 2, 3], categoryAttribute=
    ↪'CLASS_ID',
                                    resolution=Resolution(x=5, y=5).
```

Instead of explicitly specifying the rasterization `resolution`, use the `oversampling` keyword to specify the factor by which the target resolution should be oversampled. Note that if nothing is specified, an oversampling factor of 10 is used. So for example, if the target resolution is 30 m and rasterization should take place at 5 m resolution, use an oversampling factor of 6 (i.e. 30 m / 5 m = 6):

```
fractions = self.fractionArray('vector', categories=[1, 2, 3], categoryAttribute=
    ↪'CLASS_ID',
                                    oversampling=6)
```

Categories at 30 m can then be calculated from the aggregated fractions:

```
categories = numpy.array([1, 2, 3])[fractions.argmax(axis=0)]
```

2.1.11 Parallel Processing Example

Each block can be processed on a separate CPU using Python's multiprocessing module. Making use of this facility is very easy and is as simple as setting some more options on the `applier.controls` object, see `setNumThreads()`. Note, that under Windows you need to use the `if __name__ == '__main__':` statement:

```
def ufunc(operator):
    ...
    if __name__ == '__main__':
        applier = Applier()
        # ...
        applier.controls.setNumThreads(5)
        applier.apply(ufunc)
```

2.1.12 Parallel Writing Example

It is possible to have multiple writer processes. Using multiple writers (in case of multiple outputs) makes sense, because writing outputs is not only limited by the hard drive, but also by data compression and other CPU intense

overhead. Making use of this facility is also very easy and is as simple as setting some more options on the `applier.controls` object , see `setNumWriter()`:

```
applier.controls.setNumWriter(5)
```

2.1.13 Setting GDAL Options Example

Via the `applier.controls` object you can set various GDAL config options (e.g. `setGDALCacheMax()`) to handle the trade off between processing times and memory consumption:

```
applier = Applier()
applier.controls.setGDALCacheMax(bytes=1000*2**20)
applier.controls.setGDALSwathSize(bytes=1000*2**20)
applier.controls.setGDALDisableReadDirOnOpen(disable=True)
applier.controls.setGDALMaxDatasetPoolSize(nfiles=1000)
```

2.2 Data Model Usage Examples

2.2.1 Imports

Initialze notebook display

2.2.2 Testdata Overview

LT51940232010189KIS01

LT51940232010189KIS01

BrandenburgDistricts

2.2.3 Open Raster Files

2.2.4 Querying Raster Information

2.2.5 Create Raster

Understanding Formats and Drivers

When creating a new raster you have to choose a file format. Most HUB Datacube raster creation routines use the GDAL MEM format as default, which does not store the data to disc, but simply holds it in memory. This is often useful for intermediate results, testing or demonstration purposes. Different formats are provided by so called drivers. A driver can be used to create a new raster of the corresponding format.

Some drivers are subclassed...

... and provide functionality to conveniently setup some creation options.

For example, use the GTiffDriver to setup the creation options for a LZW compressed and tiled GTiff with a block size of 256. Note that the GTiffDriver exposes some enumerates for selecting appropriate creation option values (e.g. `GTiffDriver.COMPRESS.LZW`).

Raster from Array

Raster files are always associated with a pixel grid, which is defined by an extent, a resolution and a projection.

E.g., define a raster in WGS 84 projection covering the whole world with a resolution of 1°.

Create a MEM raster with random noise.

Store the raster as an ENVI file.

Store the raster as a LZW compressed GTiff file.

Create empty Raster

Write Raster Data

Using the empty raster from above.

Write red color values to the whole grid.

Write blue color values to a raster subset.

2.3 THERE IS A BUG WITH THE Y ORIGIN!!!

Write to the second rasterband creating...

2.3.1 Managing Raster Metadata

Managing Raster Metadata Items

Set some metadata items.

Query some metadata.

Specify a data type if needed.

Managing Rasterband Metadata Items

Managing No Data Values

Set a single no data value to all raster bands.

Set different no data values to each band.

Set no data values by iterating over the raster bands.

Managing Acquisition Time

Managing Descriptions

Set raster description.

Set rasterband description

Special Considerations for ENVI Software

When a raster is written

2.3.2 Read and Display Raster Data

Landsat Colored-Infrared as Multiband Color Image

Landsat CFMask as Singleband Grey Image

Landsat NDVI as Singleband Pseudocolor Image

2.3.3 Open Vector Files

2.3.4 Query Vector Information

2.3.5 Rasterize and Display Vector Data

2.3.6 Resample and Reproject Raster and Vector Data

Translate Raster Data

Warp Raster Data

Mosaic Example

Note: The user guides are created from Jupiter Notebooks. For a more interactive experience and graphical outputs execute these notebooks:

Data Model Usage Examples

2.4 Applier (hubdc.applier)

2.5 Data model (hubdc.model)

2.6 Testdata (hubdctestdata)

Two Landsat 5 scenes from the same overflight path (i.e. 194) and date (2010/189) resampled to 500 m and a vector polygon layer with the districts of Brandenburg (a federated state of Germany). The Landsat surface reflectance band names (i.e. band1, ..., band5, band7) are also assigned to more explanatory clear names (i.e. blue, green, red, nir, swir1, swir2). Reflectance values are stored as byte data, scaled between 0 and 100, with no data value set to 255.

```
class hubdc.testdata.BrandenburgDistricts
    Bases: object
    nameAttribute = 'name'
    root = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable'
```

```
shp = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'

class hubdctestdata.CFMaskCategory
    Bases: object

        Enumerate-like holding the CFMask category values.

    cloud = 4
    cloudShadow = 2
    land = 0
    snowOrIce = 3
    water = 1

class hubdctestdata.LT51940232010189KIS01
    Bases: object

        band1 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band2 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band3 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band4 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band5 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band7 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        blue = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        cfmask = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        green = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        nir = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        red = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        root = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        swirl1 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        swirl2 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'

class hubdctestdata.LT51940242010189KIS01
    Bases: object

        band1 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band2 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band3 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band4 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band5 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        band7 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        blue = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        cfmask = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        green = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
        nir = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/1'
```

```
red = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/red'
root = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable'
swir1 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/swir1'
swir2 = '/home/docs/checkouts/readthedocs.org/user_builds/hub-datacube/checkouts/stable/swir2'
```

2.7 Indices

- genindex
- modindex

Python Module Index

h

hubdctestdata, [18](#)

Index

B

band1 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band1 (hubdctestdata.LT51940242010189KIS01 attribute), 19
band2 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band2 (hubdctestdata.LT51940242010189KIS01 attribute), 19
band3 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band3 (hubdctestdata.LT51940242010189KIS01 attribute), 19
band4 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band4 (hubdctestdata.LT51940242010189KIS01 attribute), 19
band5 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band5 (hubdctestdata.LT51940242010189KIS01 attribute), 19
band7 (hubdctestdata.LT51940232010189KIS01 attribute), 19
band7 (hubdctestdata.LT51940242010189KIS01 attribute), 19
blue (hubdctestdata.LT51940232010189KIS01 attribute), 19
blue (hubdctestdata.LT51940242010189KIS01 attribute), 19
BrandenburgDistricts (class in hubdctestdata), 18

C

cfmask (hubdctestdata.LT51940232010189KIS01 attribute), 19
cfmask (hubdctestdata.LT51940242010189KIS01 attribute), 19
CFMaskCategory (class in hubdctestdata), 19
cloud (hubdctestdata.CFMaskCategory attribute), 19
cloudShadow (hubdctestdata.CFMaskCategory attribute), 19

tribute), 19

G

green (hubdctestdata.LT51940232010189KIS01 attribute), 19
green (hubdctestdata.LT51940242010189KIS01 attribute), 19

H

hubdctestdata (module), 18

L

land (hubdctestdata.CFMaskCategory attribute), 19
LT51940232010189KIS01 (class in hubdctestdata), 19
LT51940242010189KIS01 (class in hubdctestdata), 19

N

nameAttribute (hubdctestdata.BrandenburgDistricts attribute), 18
nir (hubdctestdata.LT51940232010189KIS01 attribute), 19
nir (hubdctestdata.LT51940242010189KIS01 attribute), 19

R

red (hubdctestdata.LT51940232010189KIS01 attribute), 19
red (hubdctestdata.LT51940242010189KIS01 attribute), 19
root (hubdctestdata.BrandenburgDistricts attribute), 18
root (hubdctestdata.LT51940232010189KIS01 attribute), 19
root (hubdctestdata.LT51940242010189KIS01 attribute), 20

S

shp (hubdctestdata.BrandenburgDistricts attribute), 18
snowOrIce (hubdctestdata.CFMaskCategory attribute), 19

swir1 (hubdctestdata.LT51940232010189KIS01 attribute), 19
swir1 (hubdctestdata.LT51940242010189KIS01 attribute), 20
swir2 (hubdctestdata.LT51940232010189KIS01 attribute), 19
swir2 (hubdctestdata.LT51940242010189KIS01 attribute), 20

W

water (hubdctestdata.CFMaskCategory attribute), 19