# Construction of Interactive Websites for Remote Sensing Datasets

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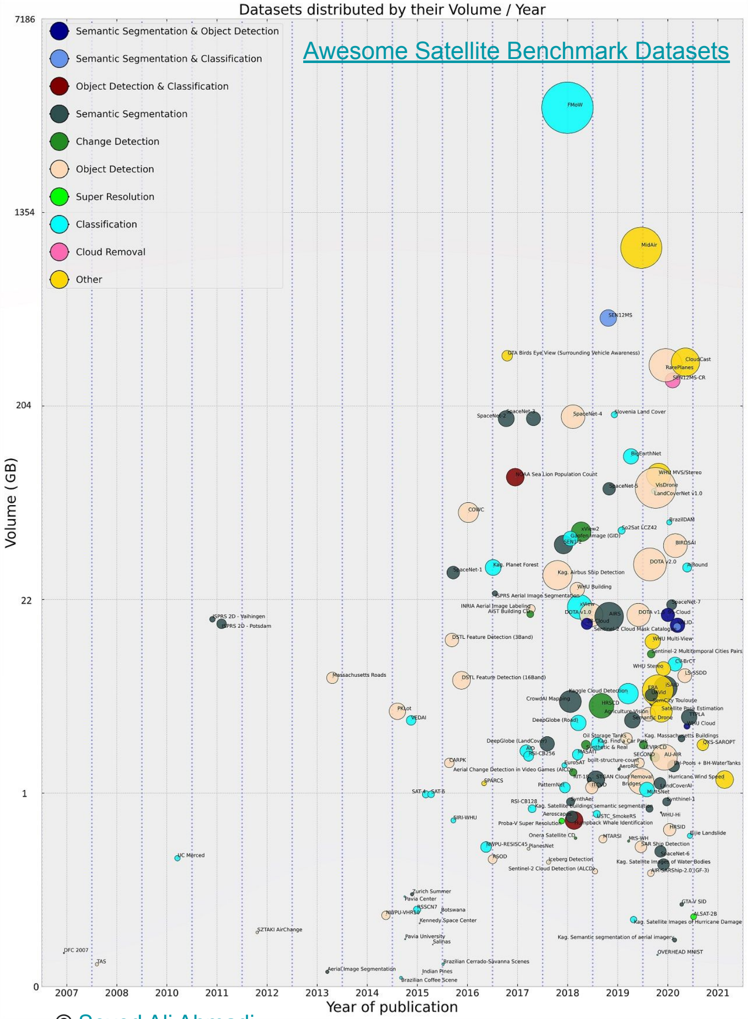
# Remote Sensing Benchmark Datasets

- To train machine learning models large-scale training datasets are required.

- Thus, several well-designed and ready-to-use benchmark datasets have been recently introduced in remote sensing.

- The descriptions of the existing datasets are often published in scientific papers as PDF files.



Awesome Satellite Benchmark Datasets

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RSiM

# Limitations of Benchmark Dataset PDFs

- **Static Format**: PDF files have no interactive visualization capabilities.
- **Page Limit**: May limit the description of the dataset due to submission guidelines.
- **Hard to update**: Once published, it is difficult to update the dataset paper/description.
- **Limited communication**: Hard to interact with the creators and users of the dataset.

## BIGEARTHNET: A LARGE-SCALE BENCHMARK ARCHIVE FOR REMOTE SENSING IMAGE UNDERSTANDING

*Gencer Sumbul* [1], *Marcela Charfuelan* [2], *Begüm Demir* [1], *Volker Markl* [1,2]

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### ABSTRACT

This paper presents the BigEarthNet that is a new large-scale multi-label Sentinel-2 benchmark archive. The BigEarthNet consists of 590, 326 Sentinel-2 image patches, each of which is a section of i) 120 × 120 pixels for 10m bands; ii) 60 × 60 pixels for 20m bands; and iii) 20 × 20 pixels for 60m bands. Unlike most of the existing archives, each image patch is annotated by multiple land-cover classes (i.e., multi-labels) that are provided from the CORINE Land Cover database of the year 2018 (CLC 2018). The BigEarthNet is significantly larger than the existing archives in remote sensing (RS) and thus is much more convenient to be used as a training source in the context of deep learning. This paper first addresses the limitations of the existing archives and then describes the properties of the BigEarthNet. Experimental results obtained in the framework of RS image scene classification problems show that a shallow Convolutional Neural Network (CNN) architecture trained on the BigEarthNet provides much higher accuracy compared to a state-of-the-art CNN model pre-trained on the ImageNet (which is a very popular large-scale benchmark archive in computer vision). The BigEarthNet opens up promising directions to advance operational RS applications and research in massive Sentinel-2 image archives.

***Index Terms*—** Sentinel-2 image archive, multi-label image classification, deep neural network, remote sensing

### 1. INTRODUCTION

Recent advances in deep learning have attracted great attention in remote sensing (RS) due to the high capability of deep networks (e.g., Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GAN)) to model the high-level semantic content of RS images. To train such networks, a very large training set is needed with a high number of annotated images in order to learn effective models with several different parameters. To the best of our knowledge, publicly available RS image archives contain only a small number of annotated images and a large-scale benchmark archive does not yet exist. Thus, the lack of a large training set is an important bottleneck that prevents the use of deep learning in RS. In order to address this problem, fine-tuning deep networks pre-trained on large-scale computer vision archives (e.g., ImageNet) is considered in RS community. However, such an approach has several limitations related to the differences on the characteristics of images between computer vision and RS. Additionally, in the existing archives, RS images are annotated by single high-level category labels that are related to the most significant content of the image. However, RS images typically contain multiple classes and thus each image can be simultaneously associated with different land-cover class labels (i.e., multi-labels). To overcome these problems, we introduce the BigEarthNet that is a new large-scale Sentinel-2 archive[1] and contains 590, 326 Sentinel-2 image patches. Each patch is annotated with multi-labels provided from the CORINE Land Cover database, which is updated in 2018 (CLC 2018). We propose our archive as a sufficient source for RS image analysis with deep learning. In order to test the BigEarthNet on RS image analysis problems, we focus our attention on image scene classification. To this end, we consider a shallow CNN architecture to be trained on the BigEarthNet. We compare the results obtained by this network with the Inception-v2 [1] pre-trained on the ImageNet. We believe that it will make a significant advancement in terms of developments of algorithms for the analysis of large-scale RS image archives.

### 2. LIMITATIONS OF EXISTING REMOTE SENSING IMAGE ARCHIVES

Most of the benchmark archives in RS (UC Merced Land Use Dataset [2], WHU-RS19 [3], RSSCN7 [4], SIRI-WHU [5], AID [6], NWPU-RESISC45 [7], RSI-CB [8], EuroSat [9] and PatternNet [10]) contain a small number of images annotated with single category labels. Table 1 presents the list of the existing archives. These archives become popular for the implementation, evaluation and validation of algorithms in the context of image classification, search and retrieval tasks. However, RS community encounters critical limitations, while using these archives for applying deep learning based approaches. One of the most critical limitations is that the number of annotated images included in the existing archives is very small. Thus, they are insufficient to train modern deep neural networks to reach a high generalization ability as the models may overfit dramatically when using small training sets. In details, training such networks on the existing archive images suffers from the problem of learning a large number

[1]The BigEarthNet is available at `http://bigearth.net`.

**Table 1**: List of the existing RS archives.

| Archive Name | Image Type | Annotation Type | Number of Images |
|---|---|---|---|
| UC Merced | Aerial RGB | Single Label [2]<br>Multi-Label [11] | 2,100<br>2,100 |
| WHU-RS19 [3] | Aerial RGB | Single Label | 1,005 |
| RSSCN7 [4] | Aerial RGB | Single Label | 2,800 |
| SIRI-WHU [5] | Aerial RGB | Single Label | 2,400 |
| AID [6] | Aerial RGB | Single Label | 10,000 |
| NWPU-RESISC45 [7] | Aerial RGB | Single Label | 31,500 |
| RSI-CB [8] | Aerial RGB | Single Label | 36,707 |
| EuroSat [9] | Satellite Multispectral | Single Label | 27,000 |
| PatternNet [10] | Aerial RGB | Single Label | 30,400 |

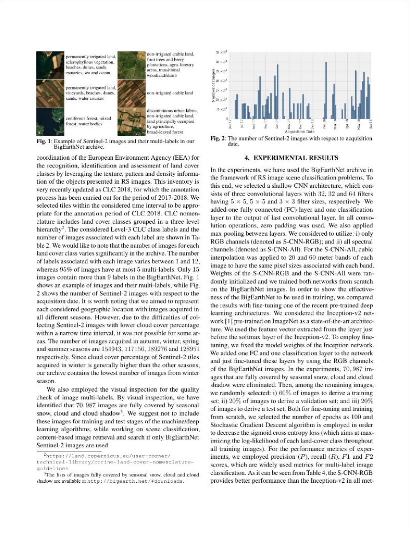
**Table 2**: The considered Level-3 CLC classes and the number of images associated with each land-cover class in the BigEarthNet.

| Land-Cover Classes | Number of Images |
|---|---|
| Mixed forest | 217, 119 |
| Coniferous forest | 211, 703 |
| Non-irrigated arable land | 196, 695 |
| Transitional woodland/shrub | 173, 506 |
| Broad-leaved forest | 150, 944 |
| Land principally occupied by agriculture, with significant areas of natural vegetation | 147, 095 |
| Complex cultivation patterns | 107, 786 |
| Pastures | 103, 554 |
| Water bodies | 83, 811 |
| Sea and ocean | 81, 612 |
| Discontinuous urban fabric | 69, 872 |
| Agro-forestry areas | 30, 674 |
| Peatbogs | 23, 207 |
| Permanently irrigated land | 13589 |
| Industrial or commercial units | 12895 |
| Natural grassland | 12, 835 |
| Olive groves | 12, 538 |
| Sclerophyllous vegetation | 11, 241 |
| Continuous urban fabric | 10, 784 |
| Water courses | 10, 572 |
| Vineyards | 9, 567 |
| Annual crops associated with permanent crops | 7, 022 |
| Inland marshes | 6, 236 |
| Moors and heathland | 5, 890 |
| Sport and leisure facilities | 5, 353 |
| Fruit trees and berry plantations | 4, 754 |
| Mineral extraction sites | 4, 618 |
| Rice fields | 3, 793 |
| Road and rail networks and associated land | 3, 384 |
| Bare rock | 3, 277 |
| Green urban areas | 1, 786 |
| Beaches, dunes, sands | 1, 578 |
| Sparsely vegetated areas | 1, 563 |
| Salt marshes | 1, 562 |
| Coastal lagoons | 1, 498 |
| Construction sites | 1, 174 |
| Estuaries | 1, 086 |
| Intertidal flats | 1, 003 |
| Airports | 979 |
| Dump sites | 959 |
| Port areas | 509 |
| Salines | 424 |
| Burnt areas | 328 |

of parameters that prevents the accurate characterization of semantic content of RS images. To this end, fine-tuning the models pre-trained on ImageNet is used as a transfer learning approach. However, the profound differences between the image properties of computer vision and RS limit the accurate characterization of RS images when fine-tuning approach is applied. As an example, Sentinel-2 images have 13 spectral bands associated to varying and lower spatial resolutions with respect to computer vision images. There are also differences in the ways that the category labels of computer vision and RS are defined for the semantic content of an image. Thus, fine-tuning pre-trained models for RS images may not be generally applicable to reduce this semantic gap and therefore may lead to weak discrimination ability for land-cover classes. Another limitation of existing archives is that they contain images annotated by single high-level category labels, which are related to the most significant content of the image. However, RS images generally contain multiple classes so that they can be simultaneously associated to different land-cover class labels (i.e., multi-labels). Hence, a benchmark archive consisting of images annotated with multi-labels is required. Although the archive presented in [11] contains images with multi-labels, the sample size of this archive is very small to be efficiently utilized for deep learning. Another limitation of RS image archives is that since researchers generally do not have free access to satellite data together with their annotation, most of the benchmark archives contain aerial images with only RGB image bands. Unavailability of a high number of annotated satellite images prevents to employ deep learning methods in a convenient way for the complete understanding of huge amount of freely accessible satellite data (e.g., Sentinel-1, Sentinel-2). Although the benchmark archive proposed in [9] includes annotated satellite images, the number of images is still small. Aforementioned limitations of existing archives reveal the need for a large-scale RS benchmark archive to be used for training deep neural networks instead of the ImageNet.

### 3. THE BIGEARTHNET ARCHIVE

To overcome the limitations of existing archives, we introduce the BigEarthNet that is the first large-scale benchmark archive in RS. We have constructed our archive by selecting 125 Sentinel-2 tiles acquired between June 2017 and May 2018. Considered tiles are distributed over the 10 countries (Austria, Belgium, Finland, Ireland, Kosovo, Lithuania, Luxembourg, Portugal, Serbia, Switzerland) of Europe. It is worth noting that considered tiles are associated to cloud cover percentage less than 1%. All tiles were atmospherically corrected by using Sentinel-2 Level 2A product generation and formatting tool (sen2cor) of ESA. Among 13 Sentinel-2 spectral bands, 10th band, for which surface information is not embodied, was excluded. After the tile selection and preliminary processing steps were carried out, selected tiles were divided into 590, 326 non-overlapping image patches. Each patch (denoted as image hereafter) is a section of i) 120 × 120 pixels for 10m bands; ii) 60 × 60 pixels for 20m bands; and iii) 20 × 20 pixels for 60m bands. We have associated each image with one or more land-cover class labels (i.e., multi-labels) provided from the CORINE Land Cover (CLC) database of the year 2018 (CLC 2018). The CLC inventory was produced by the Eionet National Reference Centres on Land Cover with the



permanently irrigated land, sclerophyllous vegetation, beaches, dunes, sands, estuaries, sea and ocean
non-irrigated arable land, fruit trees and berry plantations, agro-forestry areas, transitional woodland/shrub
permanently irrigated land, vineyards, beaches, dunes, sands, water courses
non-irrigated arable land
coniferous forest, mixed forest, water bodies
discontinuous urban fabric, non-irrigated arable land, land principally occupied by agriculture, broad-leaved forest

**Fig. 1**: Example of Sentinel-2 images and their multi-labels in our BigEarthNet archive.

Number of Images
Acquisition Date
Jun 17
Jul 17
Aug 17
Sep 17
Oct 17
Nov 17
Dec 17
Jan 18
Feb 18
Mar 18
Apr 18
May 18
Jun 18

**Fig. 2**: The number of Sentinel-2 images with respect to acquisition date.

coordination of the European Environment Agency (EEA) for the recognition, identification and assessment of land cover classes by leveraging the texture, pattern and density information of the objects presented in RS images. This inventory is very recently updated as CLC 2018, for which the annotation process has been carried out for the period of 2017-2018. We selected tiles within the considered time interval to be appropriate for the annotation period of CLC 2018. CLC nomenclature includes land cover classes grouped in a three-level hierarchy[2]. The considered Level-3 CLC class labels and the number of images associated with each label are shown in Table 2. We would like to note that the number of images for each land cover class varies significantly in the archive. The number of labels associated with each image varies between 1 and 12, whereas 95% of images have at most 5 multi-labels. Only 15 images contain more than 9 labels in the BigEarthNet. Fig. 1 shows an example of images and their multi-labels, while Fig. 2 shows the number of Sentinel-2 images with respect to the acquisition date. It is worth noting that we aimed to represent each considered geographic location with images acquired in all different seasons. However, due to the difficulties of collecting Sentinel-2 images with lower cloud cover percentage within a narrow time interval, it was not possible for some areas. The number of images acquired in autumn, winter, spring and summer seasons are 154943, 117156, 189276 and 128951 respectively. Since cloud cover percentage of Sentinel-2 tiles acquired in winter is generally higher than the other seasons, our archive contains the lowest number of images from winter season.

We also employed the visual inspection for the quality check of image multi-labels. By visual inspection, we have identified that 70, 987 images are fully covered by seasonal snow, cloud and cloud shadow[3]. We suggest not to include these images for training and test stages of the machine/deep learning algorithms, while working on scene classification, content-based image retrieval and search if only BigEarthNet Sentinel-2 images are used.

### 4. EXPERIMENTAL RESULTS

In the experiments, we have used the BigEarthNet archive in the framework of RS image scene classification problems. To this end, we selected a shallow CNN architecture, which consists of three convolutional layers with 32, 32 and 64 filters having 5 × 5, 5 × 5 and 3 × 3 filter sizes, respectively. We added one fully connected (FC) layer and one classification layer to the output of last convolutional layer. In all convolution operations, zero padding was used. We also applied max-pooling between layers. We considered to utilize: i) only RGB channels (denoted as S-CNN-RGB); and ii) all spectral channels (denoted as S-CNN-All). For the S-CNN-All, cubic interpolation was applied to 20 and 60 meter bands of each image to have the same pixel sizes associated with each band. Weights of the S-CNN-RGB and the S-CNN-All were randomly initialized and we trained both networks from scratch on the BigEarthNet images. In order to show the effectiveness of the BigEarthNet to be used in training, we compared the results with fine-tuning one of the recent pre-trained deep learning architectures. We considered the Inception-v2 network [1] pre-trained on ImageNet as a state-of-the-art architecture. We used the feature vector extracted from the layer just before the softmax layer of the Inception-v2. To employ fine-tuning, we fixed the model weights of the Inception network. We added one FC and one classification layer to the network and just fine-tuned these layers by using the RGB channels of the BigEarthNet images. In the experiments, 70, 987 images that are fully covered by seasonal snow, cloud and cloud shadow were eliminated. Then, among the remaining images, we randomly selected: i) 60% of images to derive a training set; ii) 20% of images to derive a validation set; and iii) 20% of images to derive a test set. Both for fine-tuning and training from scratch, we selected the number of epochs as 100 and Stochastic Gradient Descent algorithm is employed in order to decrease the sigmoid cross entropy loss (which aims at maximizing the log-likelihood of each land-cover class throughout all training images). For the performance metrics of experiments, we employed precision ($P$), recall ($R$), $F1$ and $F2$ scores, which are widely used metrics for multi-label image classification. As it can be seen from Table 4, the S-CNN-RGB provides better performance than the Inception-v2 in all metrics, while both networks consider only RGB image channels. When the S-CNN-All architecture is trained on the BigEarthNet images containing all spectral bands, the results become much more promising with respect to using only RGB bands. Table 3 shows the example of Sentinel-2 images with the true multi-labels and the multi-labels assigned by the Inception-v2, the S-CNN-RGB and the S-CNN-All. The performance improvements on all metrics are statistically significant under a value of $p \ll 0.0001$. The same behavior is also observed when the BigEarthnet images are associated to Level-1 and Level-2 CLC class labels. We would like to also note that the S-CNN-RGB and the S-CNN-All are very simple CNN architectures that consist of only 3 convolutional layers and max-pooling. Training deeper models (which include recent deep learning techniques such as residual connections, wider layers with varying filter sizes etc.) from scratch can lead to more promising results. On the basis of all obtained results, we can state that RS community can benefit from these pre-trained models on the BigEarthNet instead of the computer vision archives.

[2]`https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines`

[3]The lists of images fully covered by seasonal snow, cloud and cloud shadow are available at `http://bigearth.net/#downloads`.

**Table 3**: Example of Sentinel-2 images with the true multi-labels and the multi-labels assigned by the Inception-v2, the S-CNN-RGB and the S-CNN-All.

| Test Images | True Multi-Label | Inception-v2 | S-CNN-RGB | S-CNN-All |
|---|---|---|---|---|
|  | pastures, peatbogs | non-irrigated arable land, coniferous forest, mixed forest, transitional woodland/shrub | non-irrigated arable land, land occupied by agriculture, mixed forest | pastures, peatbogs |
|  | pastures, land occupied by agriculture, water bodies | coniferous forest, mixed forest, transitional woodland/shrub | non-irrigated arable land, land occupied by agriculture | pastures, land occupied by agriculture, water bodies |
|  | discontinuous urban fabric, industrial or commercial units | coniferous forest, mixed forest, transitional woodland/shrub | discontinuous urban fabric, land occupied by agriculture, broad-leaved forest, coniferous forest, mixed forest | discontinuous urban fabric, industrial or commercial units |

**Table 4**: Experimental results obtained by the Inception-v2, the S-CNN-RGB and the S-CNN-All.

| Method | $P$ (%) | $R$ (%) | $F_1$ | $F_2$ |
|---|---|---|---|---|
| Inception-v2 [1] | 48.23 | 56.79 | 0.4988 | 0.5301 |
| S-CNN-RGB | 65.06 | 75.57 | 0.6759 | 0.7139 |
| **S-CNN-All** | **69.93** | **77.10** | **0.7098** | **0.7384** |

### 5. CONCLUSION

This paper presents a large-scale benchmark archive that consists of 590, 326 Sentinel-2 image patches annotated by multi-labels for RS image understanding. We believe that the BigEarthNet will make a significant advancement for the use of deep learning in RS by overcoming the current limitations of the existing archives. Experimental results show the effectiveness of training even a simple neural network on the BigEarthNet from scratch compared to fine-tuning a state-of-the-art deep learning model pre-trained on the ImageNet. We would like to note that we plan to regularly enrich the BigEarthNet by increasing the number of annotated Sentinel-2 images.

### 6. ACKNOWLEDGEMENTS

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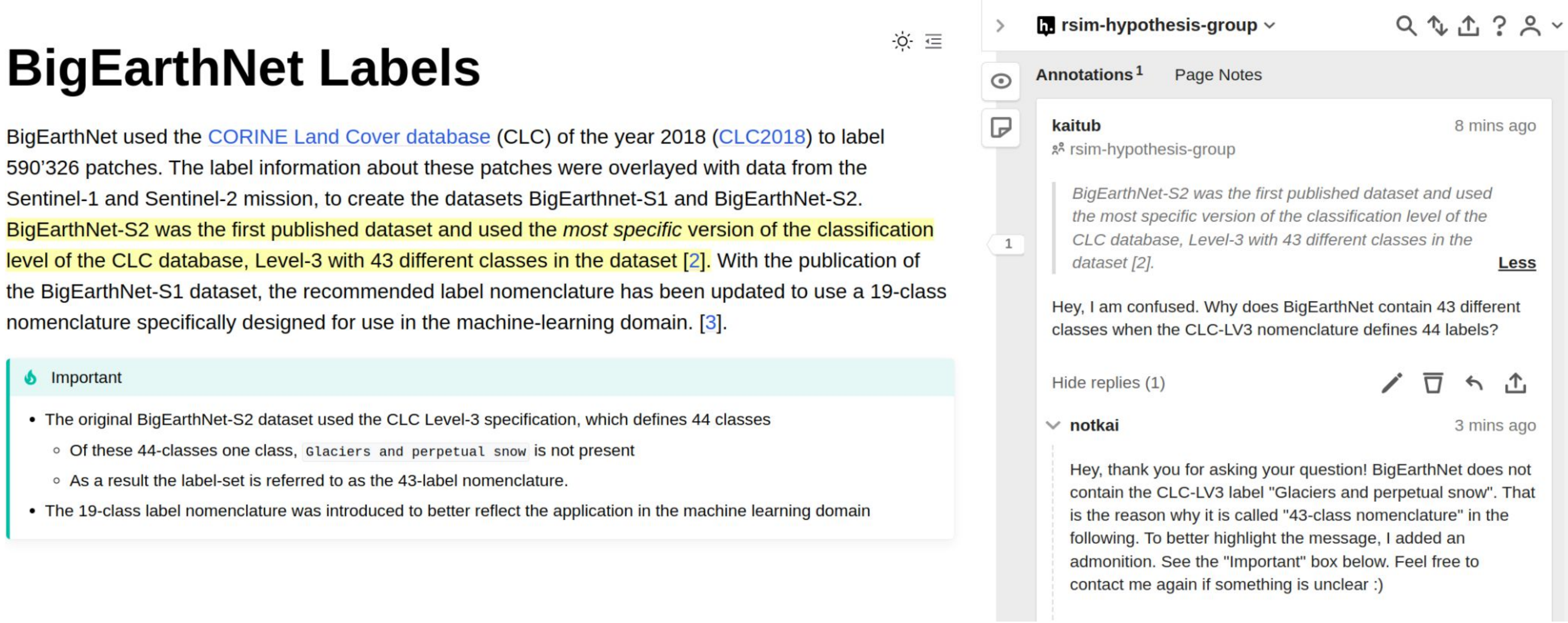
# Solution: Interactive Dataset Websites

- **Aim**: Increase accessibility through:
  - Interactive engagement of the community via commenting systems.



## BigEarthNet Labels

BigEarthNet used the CORINE Land Cover database (CLC) of the year 2018 (CLC2018) to label 590'326 patches. The label information about these patches were overlayed with data from the Sentinel-1 and Sentinel-2 mission, to create the datasets BigEarthnet-S1 and BigEarthNet-S2. BigEarthNet-S2 was the first published dataset and used the *most specific* version of the classification level of the CLC database, Level-3 with 43 different classes in the dataset [2]. With the publication of the BigEarthNet-S1 dataset, the recommended label nomenclature has been updated to use a 19-class nomenclature specifically designed for use in the machine-learning domain. [3].

> Important
>
> - The original BigEarthNet-S2 dataset used the CLC Level-3 specification, which defines 44 classes
>   - Of these 44-classes one class, `Glaciers and perpetual snow` is not present
>   - As a result the label-set is referred to as the 43-label nomenclature.
> - The 19-class label nomenclature was introduced to better reflect the application in the machine learning domain

**kaitub** 8 mins ago
rsim-hypothesis-group

> *BigEarthNet-S2 was the first published dataset and used the most specific version of the classification level of the CLC database, Level-3 with 43 different classes in the dataset [2].* Less

Hey, I am confused. Why does BigEarthNet contain 43 different classes when the CLC-LV3 nomenclature defines 44 labels?

Hide replies (1)

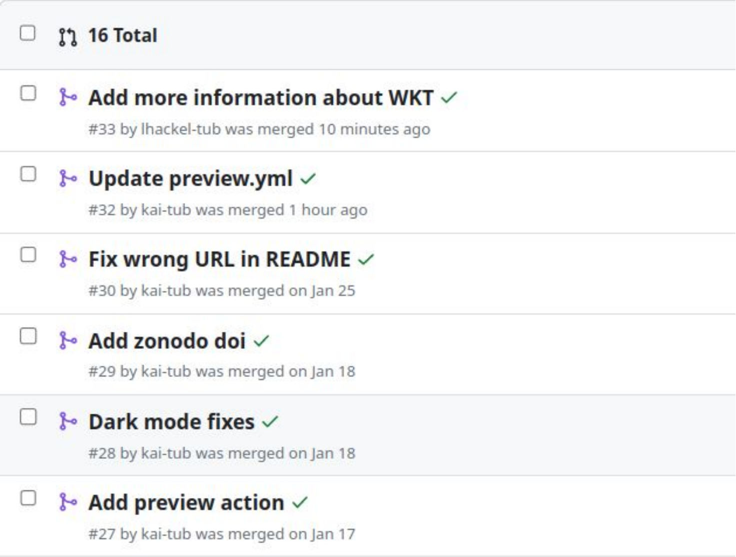
**notkai** 3 mins ago

Hey, thank you for asking your question! BigEarthNet does not contain the CLC-LV3 label "Glaciers and perpetual snow". That is the reason why it is called "43-class nomenclature" in the following. To better highlight the message, I added an admonition. See the "Important" box below. Feel free to contact me again if something is unclear :)

RSiM

# Solution: Interactive Dataset Websites

- **Aim**: Increase accessibility through:
  - Allow community to contribute to the project.



□ Add more information about WKT ✓
#33 by lhackel-tub was merged 10 minutes ago

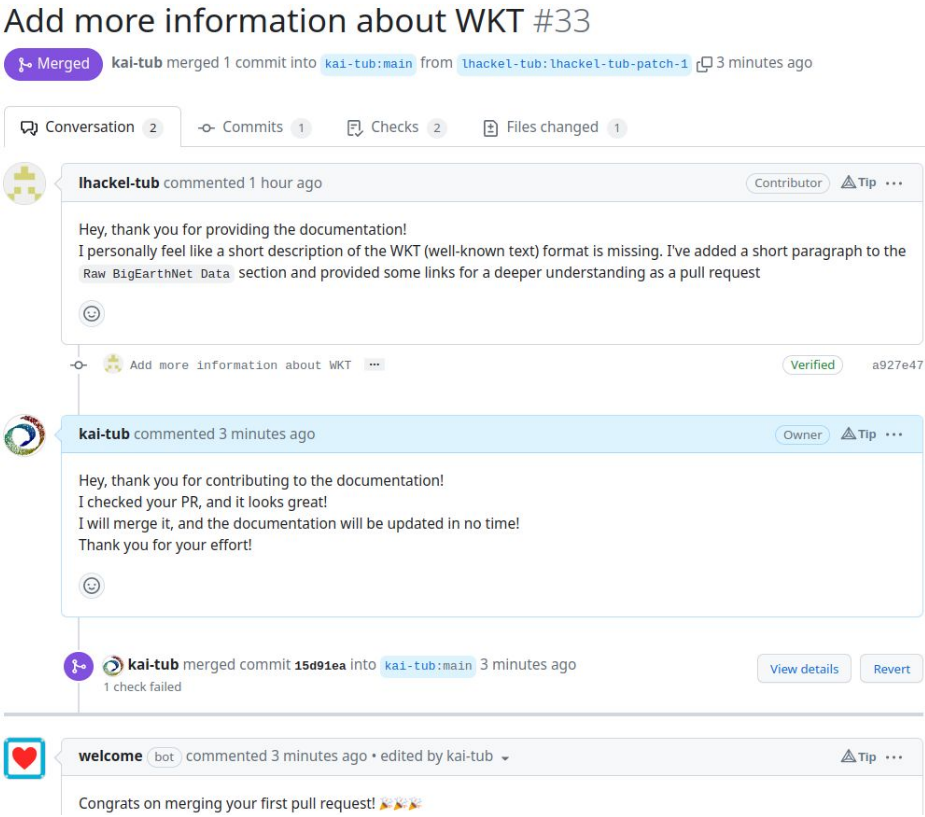
□ Update preview.yml ✓
#32 by kai-tub was merged 1 hour ago

□ Fix wrong URL in README ✓
#30 by kai-tub was merged on Jan 25

□ Add zonodo doi ✓
#29 by kai-tub was merged on Jan 18

□ Dark mode fixes ✓
#28 by kai-tub was merged on Jan 18

□ Add preview action ✓
#27 by kai-tub was merged on Jan 17



Add more information about WKT #33

Merged kai-tub merged 1 commit into `kai-tub:main` from `lhackel-tub:lhackel-tub-patch-1` 3 minutes ago

**lhackel-tub** commented 1 hour ago · Contributor · Tip ···

Hey, thank you for providing the documentation!
I personally feel like a short description of the WKT (well-known text) format is missing. I've added a short paragraph to the `Raw BigEarthNet Data` section and provided some links for a deeper understanding as a pull request

`Add more information about WKT` ··· Verified a927e47

**kai-tub** commented 3 minutes ago · Owner · Tip ···

Hey, thank you for contributing to the documentation!
I checked your PR, and it looks great!
I will merge it, and the documentation will be updated in no time!
Thank you for your effort!

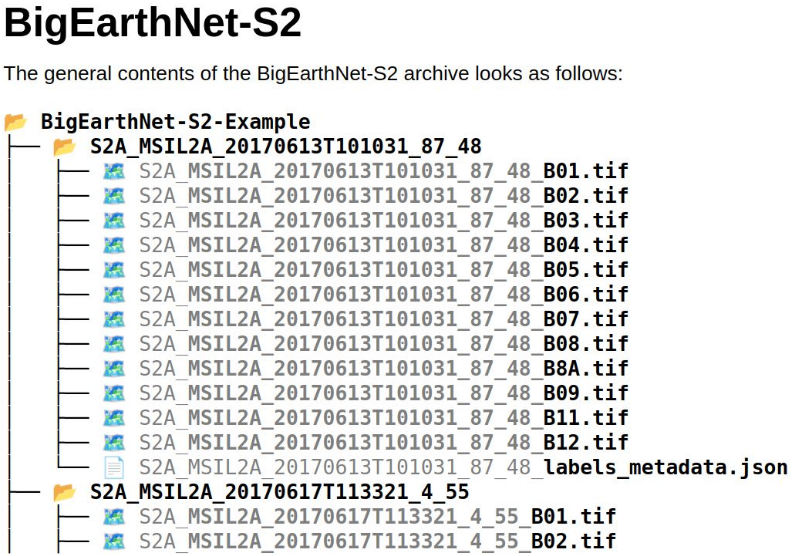
**kai-tub** merged commit **15d91ea** into `kai-tub:main` 3 minutes ago
1 check failed

**welcome** bot commented 3 minutes ago • edited by kai-tub · Tip ···

Congrats on merging your first pull request! 🎉🎉🎉

# Solution: Interactive Dataset Websites

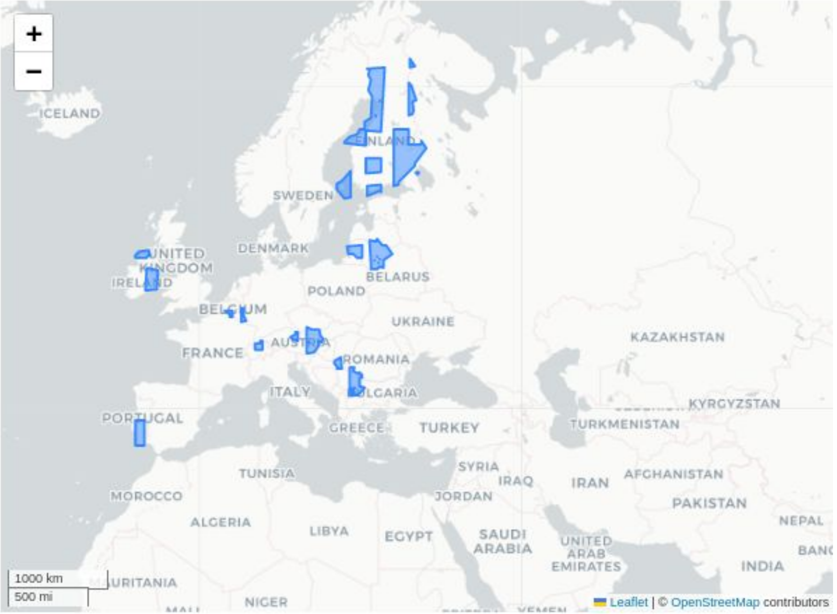
- **Aim**: Increase accessibility through:
  - Illustrative and interactive visualizations.



## BigEarthNet-S2

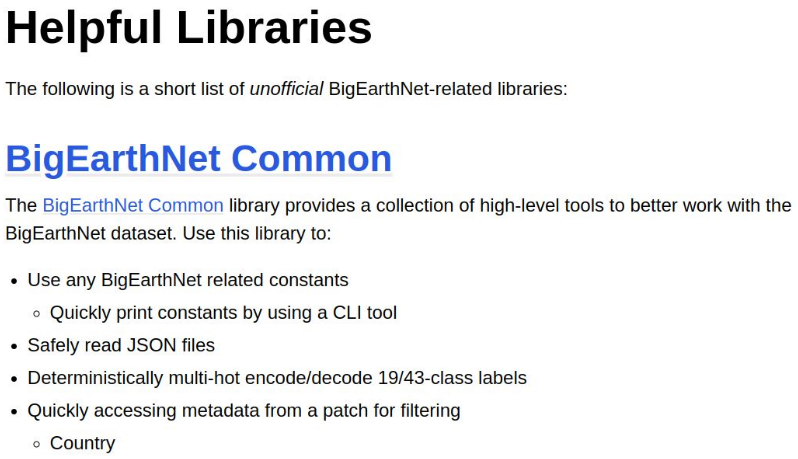
The general contents of the BigEarthNet-S2 archive looks as follows:

```
📂 BigEarthNet-S2-Example
├── 📂 S2A_MSIL2A_20170613T101031_87_48
│   ├── S2A_MSIL2A_20170613T101031_87_48_B01.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B02.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B03.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B04.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B05.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B06.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B07.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B08.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B8A.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B09.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B11.tif
│   ├── S2A_MSIL2A_20170613T101031_87_48_B12.tif
│   └── S2A_MSIL2A_20170613T101031_87_48_labels_metadata.json
├── 📂 S2A_MSIL2A_20170617T113321_4_55
│   ├── S2A_MSIL2A_20170617T113321_4_55_B01.tif
│   ├── S2A_MSIL2A_20170617T113321_4_55_B02.tif
```



# Solution: Interactive Dataset Websites

- **Aim**: Increase accessibility through:
  - Example code for using, loading and visualizing the data;
  - Providing links to useful tools/libraries to work with the datasets.



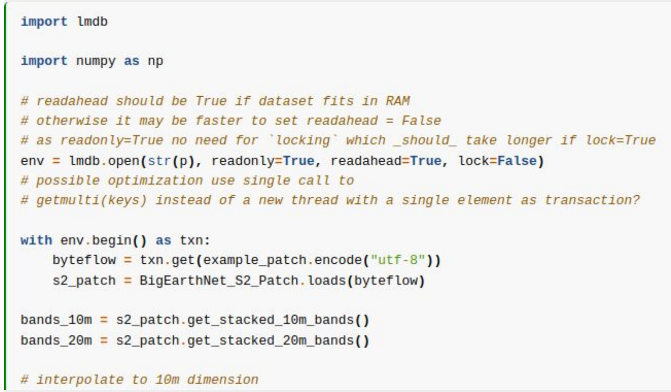
## Helpful Libraries

The following is a short list of *unofficial* BigEarthNet-related libraries:

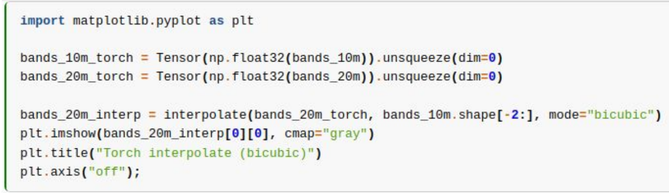
### BigEarthNet Common

The BigEarthNet Common library provides a collection of high-level tools to better work with the BigEarthNet dataset. Use this library to:

- Use any BigEarthNet related constants
  - Quickly print constants by using a CLI tool
- Safely read JSON files
- Deterministically multi-hot encode/decode 19/43-class labels
- Quickly accessing metadata from a patch for filtering
  - Country



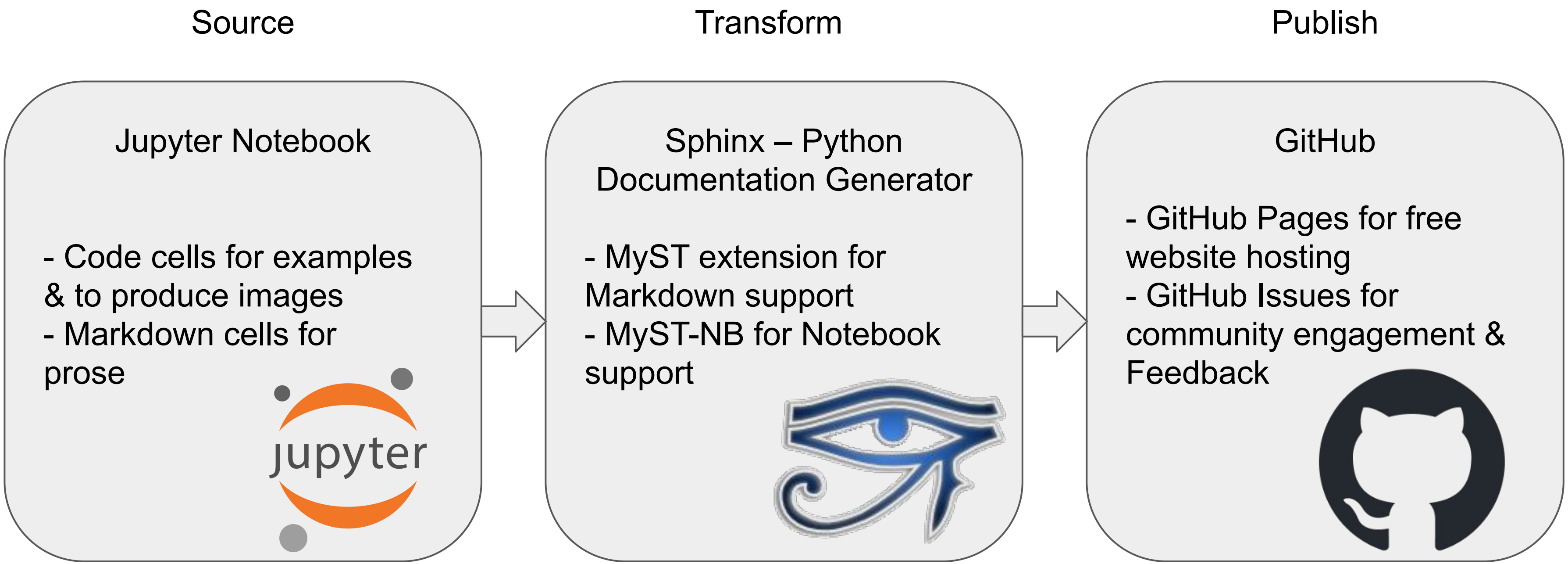
```
import lmdb

import numpy as np

# readahead should be True if dataset fits in RAM
# otherwise it may be faster to set readahead = False
# as readonly=True no need for `locking` which _should_ take longer if lock=True
env = lmdb.open(str(p), readonly=True, readahead=True, lock=False)
# possible optimization use single call to
# getmulti(keys) instead of a new thread with a single element as transaction?

with env.begin() as txn:
    byteflow = txn.get(example_patch.encode("utf-8"))
    s2_patch = BigEarthNet_S2_Patch.loads(byteflow)

bands_10m = s2_patch.get_stacked_10m_bands()
bands_20m = s2_patch.get_stacked_20m_bands()

# interpolate to 10m dimension
```



```
import matplotlib.pyplot as plt

bands_10m_torch = Tensor(np.float32(bands_10m)).unsqueeze(dim=0)
bands_20m_torch = Tensor(np.float32(bands_20m)).unsqueeze(dim=0)

bands_20m_interp = interpolate(bands_20m_torch, bands_10m.shape[-2:], mode="bicubic")
plt.imshow(bands_20m_interp[0][0], cmap="gray")
plt.title("Torch interpolate (bicubic)")
plt.axis("off");
```

Torch interpolate (bicubic)

# Suggested Workflow with Open-Source Tools



Source

Jupyter Notebook

- Code cells for examples & to produce images
- Markdown cells for prose

Transform

Sphinx – Python Documentation Generator

- MyST extension for Markdown support
- MyST-NB for Notebook support

Publish

GitHub

- GitHub Pages for free website hosting
- GitHub Issues for community engagement & Feedback

# Interactive Dataset Websites like docs.kai-tub.tech/ben-docs

=

# More accessible and engaging science

SCAN ME

# Acknowledgement

Bundesministerium
für Wirtschaft
und Klimaschutz

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# Additional Material

# Jupyter Project

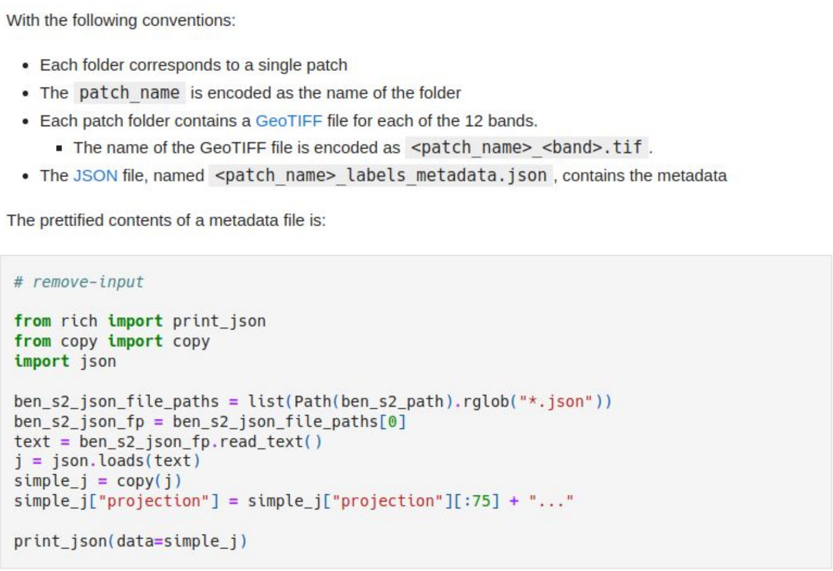
- A Jupyter Notebook is a web-based interactive computing platform that allows users to create and share documents that combine live code, equations, visualizations, and narrative text.

- Notebooks provide an easy way to prototype, experiment, and iterate on data analysis and machine learning models.

- Additional links:
  - [Official Jupyter Project Documentation]
  - [Try Jupyter on the web without installing anything]
  - [Example Jupyter Lab Notebook]

# Jupyter NB source to HTML page I

## Source File



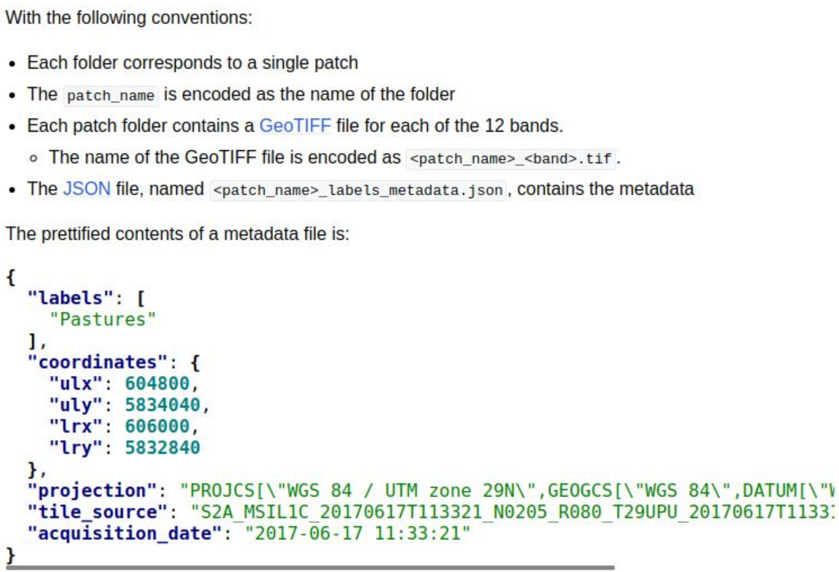
With the following conventions:

- Each folder corresponds to a single patch
- The `patch_name` is encoded as the name of the folder
- Each patch folder contains a GeoTIFF file for each of the 12 bands.
  - The name of the GeoTIFF file is encoded as `<patch_name>_<band>.tif`.
- The JSON file, named `<patch_name>_labels_metadata.json`, contains the metadata

The prettified contents of a metadata file is:

```python
# remove-input

from rich import print_json
from copy import copy
import json

ben_s2_json_file_paths = list(Path(ben_s2_path).rglob("*.json"))
ben_s2_json_fp = ben_s2_json_file_paths[0]
text = ben_s2_json_fp.read_text()
j = json.loads(text)
simple_j = copy(j)
simple_j["projection"] = simple_j["projection"][:75] + "..."

print_json(data=simple_j)
```

## HTML Page



With the following conventions:

- Each folder corresponds to a single patch
- The `patch_name` is encoded as the name of the folder
- Each patch folder contains a GeoTIFF file for each of the 12 bands.
  - The name of the GeoTIFF file is encoded as `<patch_name>_<band>.tif`.
- The JSON file, named `<patch_name>_labels_metadata.json`, contains the metadata

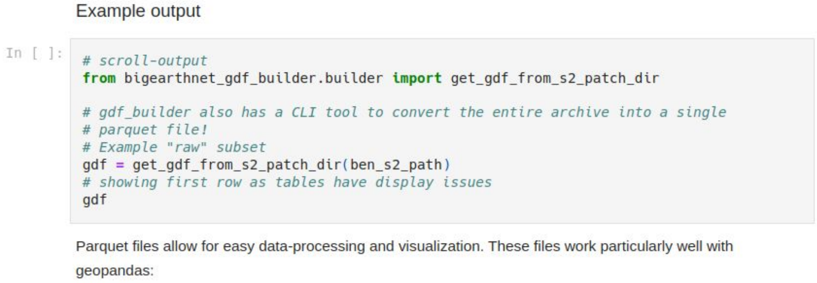
The prettified contents of a metadata file is:

```
{
  "labels": [
    "Pastures"
  ],
  "coordinates": {
    "ulx": 604800,
    "uly": 5834040,
    "lrx": 606000,
    "lry": 5832840
  },
  "projection": "PROJCS[\"WGS 84 / UTM zone 29N\",GEOGCS[\"WGS 84\",DATUM[\"W
  "tile_source": "S2A_MSIL1C_20170617T113321_N0205_R080_T29UPU_20170617T1133
  "acquisition_date": "2017-06-17 11:33:21"
}
```

RSiM

# Jupyter NB source to HTML page II

Source File

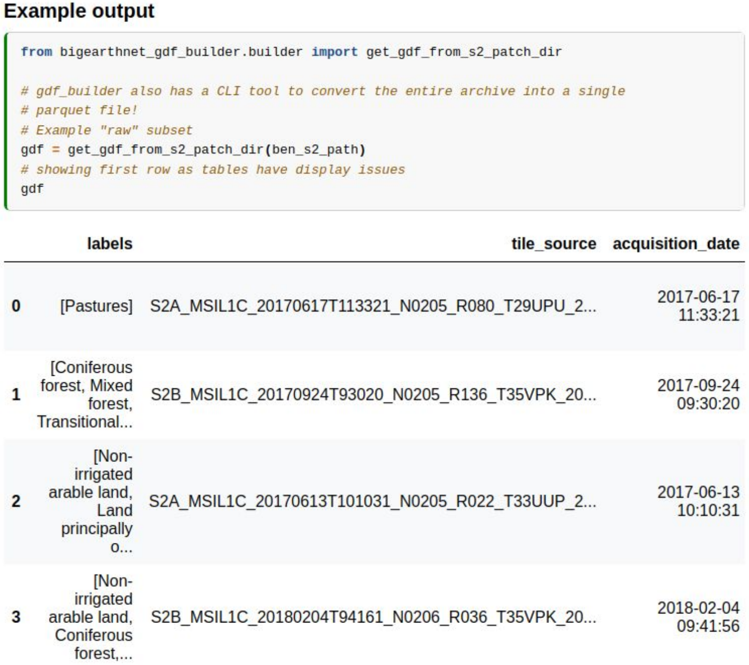


Example output

```
In [ ]:
# scroll-output
from bigearthnet_gdf_builder.builder import get_gdf_from_s2_patch_dir

# gdf_builder also has a CLI tool to convert the entire archive into a single
# parquet file!
# Example "raw" subset
gdf = get_gdf_from_s2_patch_dir(ben_s2_path)
# showing first row as tables have display issues
gdf
```

Parquet files allow for easy data-processing and visualization. These files work particularly well with geopandas:

HTML Page



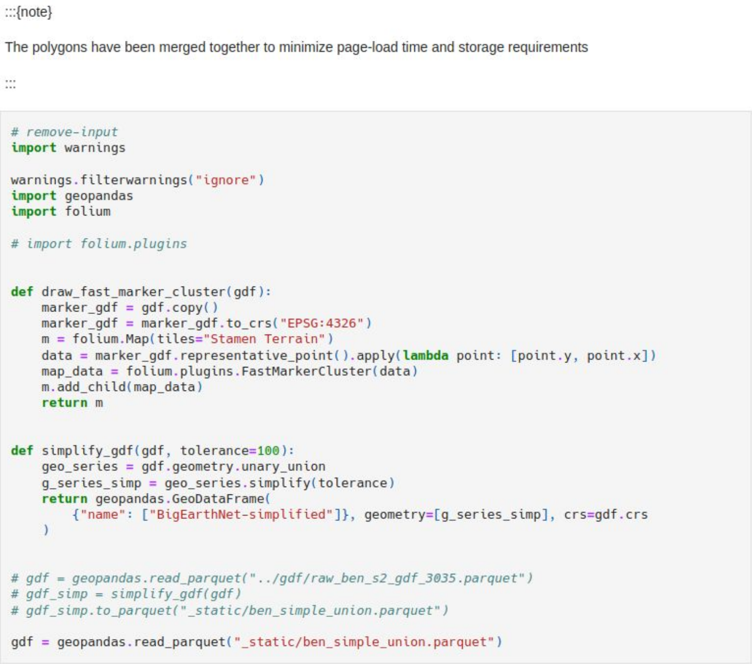
**Example output**

```
from bigearthnet_gdf_builder.builder import get_gdf_from_s2_patch_dir

# gdf_builder also has a CLI tool to convert the entire archive into a single
# parquet file!
# Example "raw" subset
gdf = get_gdf_from_s2_patch_dir(ben_s2_path)
# showing first row as tables have display issues
gdf
```

| | labels | tile_source | acquisition_date |
|---|---|---|---|
| **0** | [Pastures] | S2A_MSIL1C_20170617T113321_N0205_R080_T29UPU_2... | 2017-06-17 11:33:21 |
| **1** | [Coniferous forest, Mixed forest, Transitional... | S2B_MSIL1C_20170924T93020_N0205_R136_T35VPK_20... | 2017-09-24 09:30:20 |
| **2** | [Non-irrigated arable land, Land principally o... | S2A_MSIL1C_20170613T101031_N0205_R022_T33UUP_2... | 2017-06-13 10:10:31 |
| **3** | [Non-irrigated arable land, Coniferous forest,... | S2B_MSIL1C_20180204T94161_N0206_R036_T35VPK_20... | 2018-02-04 09:41:56 |

# Jupyter NB source to HTML page III

## Source File



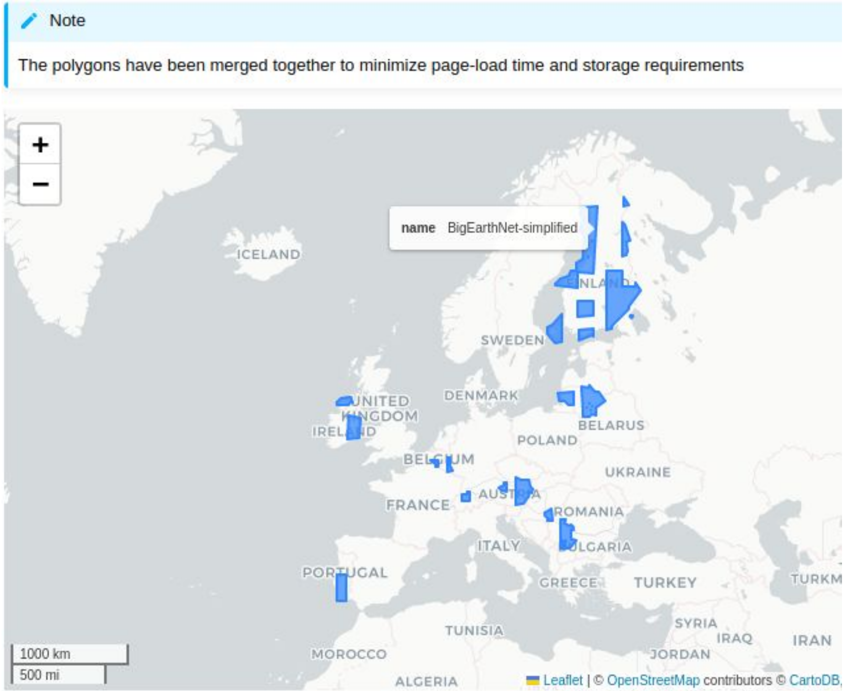
:::{note}

The polygons have been merged together to minimize page-load time and storage requirements

:::

```
# remove-input
import warnings

warnings.filterwarnings("ignore")
import geopandas
import folium

# import folium.plugins


def draw_fast_marker_cluster(gdf):
    marker_gdf = gdf.copy()
    marker_gdf = marker_gdf.to_crs("EPSG:4326")
    m = folium.Map(tiles="Stamen Terrain")
    data = marker_gdf.representative_point().apply(lambda point: [point.y, point.x])
    map_data = folium.plugins.FastMarkerCluster(data)
    m.add_child(map_data)
    return m


def simplify_gdf(gdf, tolerance=100):
    geo_series = gdf.geometry.unary_union
    g_series_simp = geo_series.simplify(tolerance)
    return geopandas.GeoDataFrame(
        {"name": ["BigEarthNet-simplified"]}, geometry=[g_series_simp], crs=gdf.crs
    )


# gdf = geopandas.read_parquet("../gdf/raw_ben_s2_gdf_3035.parquet")
# gdf_simp = simplify_gdf(gdf)
# gdf_simp.to_parquet("_static/ben_simple_union.parquet")

gdf = geopandas.read_parquet("_static/ben_simple_union.parquet")
```

## HTML Page



Note

The polygons have been merged together to minimize page-load time and storage requirements

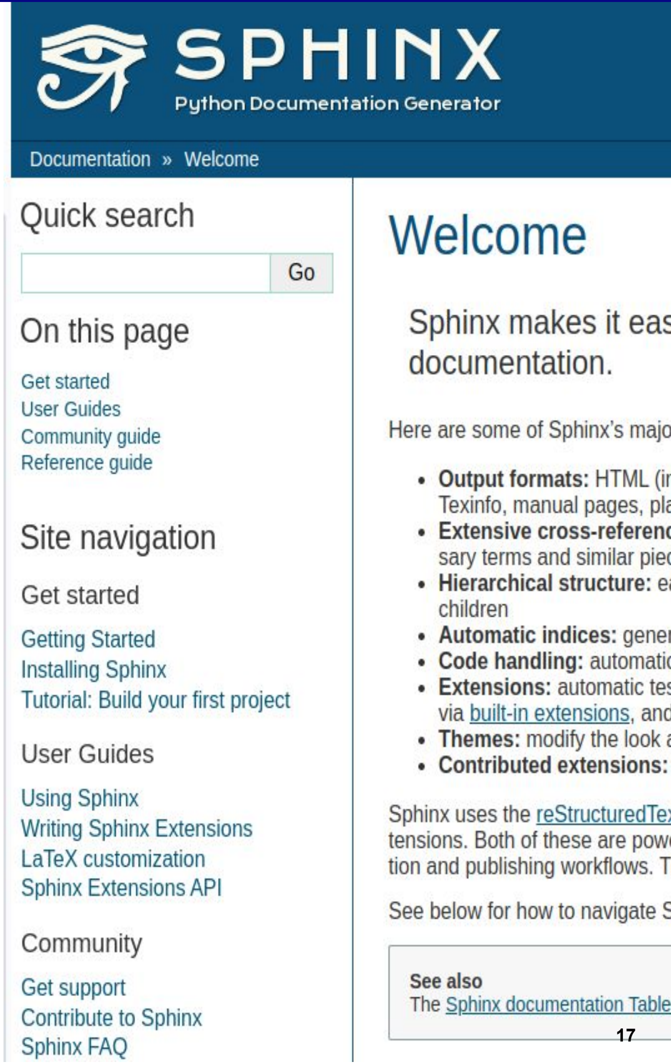
# Executable Books Project

- The Executable Books Project is an open-source project that aims to improve the sustainability of scientific research by developing tools that facilitate publishing computational narratives using the Jupyter ecosystem, such as:
    - Jupyter Books
    - MyST-NB project

- Additional links:
    - Official Executable Books Documentation
    - Jupyter Book Gallery
    - MyST (Markedly Structured Text) – A superset of the CommonMark language

- Sphinx is an open-source documentation generator that:
  - is widely used in the Python community, but can also be used for other programming languages;
  - is used as the foundation for many Executable Book Projects/Tools.

- Additional Links:
  - Official Sphinx Documentation
  - Furo – A popular Sphinx Theme (also used for the BigEarthNet Guide)
  - Using Markdown (MyST) in Sphinx instead of *reStructured Text* (reST)



On this page

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User Guides
Community guide
Reference guide

Site navigation

Get started

Getting Started
Installing Sphinx
Tutorial: Build your first project

User Guides

Using Sphinx
Writing Sphinx Extensions
LaTeX customization
Sphinx Extensions API

Community

Get support
Contribute to Sphinx
Sphinx FAQ

Welcome

Sphinx makes it eas
documentation.

Here are some of Sphinx's majo

- **Output formats:** HTML (ir
Texinfo, manual pages, pla
- **Extensive cross-referenc**
sary terms and similar piec
- **Hierarchical structure:** ea
children
- **Automatic indices:** gener
- **Code handling:** automatic
- **Extensions:** automatic tes
via built-in extensions, and
- **Themes:** modify the look a
- **Contributed extensions:**

Sphinx uses the reStructuredTe
tensions. Both of these are pow
tion and publishing workflows. T

See below for how to navigate S

**See also**
The Sphinx documentation Table

# GitHub Pages

- *GitHub Pages* is a free web hosting service provided by GitHub that:
  - allows users to create static websites and host them on GitHub's servers;
  - supports a variety of static site generators, such as Sphinx and Jekyll

- Additional links:
  - Official GitHub Pages Documentation
  - Using a custom domain for your GitHub Pages site
  - GitHub Pages usage limits