

# Material Fractional Cover Algorithm

By: ASU Carbon Mapper Land and Ocean Team

Version 1.0

## 1. Algorithm Description

### 1.1. Objective

The objective of the Material Fractional Cover (MFC) algorithm is to compute the per pixel fractional coverage of selected material classes (Table 1.1) from Carbon Mapper imaging spectroscopy data by means of Multiple Endmember Spectral Mixture Analysis (MESMA), and to predict the dominant material class per image pixel. The algorithm is supposed to be extendable by custom spectral libraries and should allow for retrieving of additional semantic information beyond the class level (e.g., if a photosynthetic vegetation spectrum belongs to a tree or a shrub).

Table 1.1. List of selected material classes<sup>1</sup>.

| MaterialClass                       |
|-------------------------------------|
| Asphalt                             |
| Brick                               |
| Concrete                            |
| Metal                               |
| Natural Substrate                   |
| Non-photosynthetic vegetation (NPV) |
| Other man-made materials            |
| Plastic                             |
| Photosynthetic Vegetation (PV)      |
| Water                               |

### 1.2 Theoretical Background

MESMA is a spectral unmixing algorithm first described by Roberts et al. (1998). It is an extension of simple Spectral Mixture Analysis (SMA) and shares the basic assumption that the spectral reflectance in a pixel can be modeled by linear combination of pure endmember reflectance spectra representing the

---

<sup>1</sup> This list was agreed on after the presentation of the development team on Oct 24, 2022.

abundant surface types weighted by their respective fractional coverage. MESMA extends SMA by enabling the number of classes and selected endmembers per class to vary on a per-pixel basis. It is a well-established algorithm and has been used in combination with case-specific spectral libraries (SLIs) for numerous different purposes including oil detection in coastal marsh lands (Petersen et al. 2015), melt pond fraction analysis on Arctic sea ice (Yackel et al. 2017), mapping of Eucalyptus subgenera (Youngentob et al. 2011), differentiating plant species within and across ecosystems (Roth et al. 2015), mapping land-cover types in a desert city (Myint and Okin 2009) and mapping spectrally similar urban materials (Wetherley et al. 2017).

Inputs to MESMA are: 1) an image to be unmixed and 2) an SLI of pure spectral endmembers associated with semantic classes of interest. For each image pixel, MESMA simulates mixed spectra using all possible combinations of spectral endmembers from different classes, along with shade fraction represented as an additional endmember of constant reflectance (see Section 1.4.3 for more detail). The combination of endmembers that results in the smallest root mean squared error (RMSE) between the simulated and the measured spectrum is retained along with their respective fractional coverage. If not specified otherwise, MESMA will always unmix a pixel spectrum with as few endmembers as possible, only selecting more complex models if the RMSE difference exceeds a user-defined threshold which is called the fusion value. In practice, this means that MESMA will first try to model each pixel spectrum with only one spectrum from the SLI and a shade fraction; this is called a two-endmember (2-EM) model. In the next step, MESMA then models each pixel spectrum as a combination of endmembers from two classes plus a shade fraction (3-EM model). A 3-EM model will only be accepted as superior to a 2-EM model if the RMSE of the 3-EM model is smaller than the RMSE of the 2-EM model by at least the fusion value. Theoretically, any level of endmember complexity is possible. Depending on data dimensionality and SLI complexity, however, higher levels are often limited by computational resources because the number of possible endmember combinations can quickly become very extensive with many spectra and classes in the SLI.

The per-pixel outputs of MESMA are 1) the endmembers resulting in the smallest RMSE, 2) the fractional coverage of the respective classes, and 3) the corresponding RMSE. In addition, MESMA may return a residual image 4) and the fractional coverage output can be translated into a hard classification 5), i.e., each pixel is assigned the class with the highest fractional coverage. See Section 2.3 for details.

## 1.3 Spectral Library

The SLI is a critical factor for the performance of any SMA including MESMA. It must contain representative pure spectra that cover the spectral variability for all semantic classes of interest present in a particular image. At the same time, a SLI should be as small as possible for the above-mentioned computational reasons.

SLI endmembers may either be spectra gathered with field or lab spectrometers or may be retrieved from pure image pixels, whereby adequate spatial resolution depends on the relative size of the target surfaces. The former has the virtue that pure small size samples can be acquired under controlled conditions (e.g., illumination conditions) while the latter has the advantage that system-inherent artifacts (e.g., resulting from sensor calibration or atmospheric correction) are incorporated in the data. Thus, endmembers extracted from imagery may be more appropriate for unmixing of other pixels from the same image. A

major drawback of image-based endmember extraction is that semantic information about pixels is often not available in the desired level of detail, possibly requiring time and labor-intensive field data acquisition or expert knowledge. For example, it may be easy to visually identify a pixel as a roof but challenging to identify the material it is made of.

Because a globally applicable algorithm theoretically needs to cover the vast spectral variability present in all regions of the world, we reviewed six publicly available SLIs from different regions of the world for their suitability (see Table 2.2.1 and Secs. 2.2.1 – 2.2.6 for technical details). Some SLIs are tailored to certain regions in the sense that SLI endmembers represent typical semantic classes present in the region of data collection (e.g., endmembers in the Karlsruhe Library of Urban Materials represent materials prevalent in Germany, Section 2.2.2), while others are compilations of endmembers from different regions (e.g., the ECOSTRESS Spectral Library, Section 2.2.6). Eventually, we harmonized spectra from three publicly available SLIs and enriched this compilation with spectral endmembers retrieved from visual-to-shortwave infrared (VSWIR) imaging spectroscopy data acquired with the Global Airborne Observatory (GAO) in the city of Phoenix, Arizona (Section 2.2.7). This comprehensive compiled SLI (Carbon Mapper SLI) consists of 2252 endmembers from 10 semantic classes (Table 1.1).

## 1.4 Spectral Library Pruning

SLI pruning is a common preprocessing step in SMA that aims to reduce the number of endmembers used for unmixing by discarding image-irrelevant and redundant spectra from the SLI, while avoiding spectral confusion. While large SLIs often contain more spectra than needed for land cover mapping of specific sites, a globally applicable algorithm with the potential to provide detailed semantic information beyond the class level to some extent contradicts the idea of SLI pruning because removal of endmembers prohibits extracting the associated higher-level information. For example, few spectra of photosynthetic vegetation may be sufficient to represent this semantic class but a specific endmember may be necessary to identify a pixel as a certain type of tree. For this reason, no SLI pruning is applied in this version of the MFC algorithm.

## 1.4 Assumptions and Limitations

### 1.4.1 Material Detection

MESMA is not initially designed as a material detection algorithm. Although under certain circumstances MESMA may have the capability to detect abundant materials on a sub-pixel scale through spectral unmixing, however it is not a detection system such as Tetracorder (Clark et al. 2003). A specific material is only detected if the corresponding endmember is part of the endmember model resulting in the smallest RMSE, i.e., its influence on the spectral mixture needs to be substantial which depends on both its fractional coverage and its spectral dissimilarity to other material classes contributing to the mixed signal. In addition, the relative influence of an endmember on the spectral mixture may be wavelength-dependent. MESMA uses all bands provided to compute the RMSE between measured and simulated spectra but some classes may be only separable (i.e., breach the pre-defined RMSE threshold) in certain wavelength regions. There are methods to optimize band selection or weighting for unmixing (e.g., Somers et al. 2009, 2010) but these approaches are based on spectral similarity of within-class

endmembers and dissimilarity of spectra between classes. This prerequisite, however, is not naturally given for many semantic classes. A generic, globally applicable approach, thus, will be limited to provide the fractional coverage of only a few dominant spectral classes in each pixel.

### 1.4.2 Semantic vs. Spectral Segmentation of SLIs

Semantic segmentation of the compiled SLI (Secs. 1.3, 2.2) is not based on spectral characteristics. Yet, a certain degree of inter-class separability and intra-class homogeneity is important to avoid spectral confusion, and consequently is a prerequisite for optimizing spectral band selection in SMA. For example, the class *Other man-made* is characterized by a large intra-class spectral variability across all bands which hampers application of the above-mentioned optimization algorithms.

Improved spectral segmentation of a SLI may be achieved e.g., by clustering similar spectra based on spectral distance metrics (Loughlin et al. 2020). The resulting clusters, however, may not necessarily match the desired semantic classes that users or customers are interested in.

### 1.4.3 Shade

In addition to a combination of one or more endmember spectra from the SLI, MESMA also fits a shade fraction during the optimization process. If not specified otherwise, shade fraction is a spectrally-uniform endmember of zero reflectance (photometric shade). Traditionally, the fractional cover of shade is allowed to vary between 0 and 0.8 (=80%) (see Table 2.2.1 for details). Yet, negative shade may be required if endmembers do not represent the brightest possible reflectance of a material and high shade fractions may enable spectral confusion, e.g., if a dark endmember can be modeled using a bright endmember with shade.

Enriching the combined SLI with image spectra required selecting spectra from bright white roofs but the selected spectra did not represent the brightest version of the associated material (Section 2.2.7). Thus, we allowed for shade to be negative (-0.1), i.e., brightening of endmember spectra and mixtures. For surfaces that are primarily distinguishable according to their brightness but not due to their spectral shape (e.g., some asphalt and concrete endmembers), however, loosening the shade constraint may enable more possible solutions of MESMA.

### 1.4.4 Map Grid Cell Size

Depending on the spectral complexity in a pixel, i.e., the number of classes and the degree of their spectral separability, the spatial resolution or map grid cell size impacts the performance of SMA (Wetherley et al. 2017). For large uniform landscapes consisting of very few spectrally dissimilar classes (e.g., deep dark water and bright snow in Arctic sea ice) SMA may still perform well even if grid cell size is large. Environments characterized by many small size features of partial high spectral similarity (e.g., cities) SMA is challenging. Because the number of possible endmember classes per pixel in MESMA is limited, only the spectrally most prominent classes will be reported, while surface classes with small fractional coverage or small influence on the mixed signal may not be accounted for. A particular challenge arises if the mixed spectral signal of multiple endmembers resembles the spectral shape of a pure endmember. In this case, MESMA will prefer the solution with the fewest endmembers under consideration of the fusion value if not specified otherwise (see Section 1.2).

### 1.4.1 Performance Assessment

Multiple criteria may be used to assess the performance of a classification model. The most frequently used performance criteria for per-class performance assessment are precision, recall and f1-score.

Precision is the probability that a value in a given class was classified correctly and is mathematically defined as the ratio of values that were correctly assigned to a given class and all values assigned to the same class. It describes the model's ability to avoid false positives. Recall is the probability that a value predicted to be in a certain class really is that class, and is mathematically defined as the ratio of correctly assigned values to the sum of correctly assigned and incorrectly not unassigned values. It describes the model's ability to find all the positive samples. f1-score is the harmonic mean of precision and recall.

## 2. Technical Details

The MaterialFractionalCover Github repository<sup>2</sup> contains three iPython notebooks that include example code to run MESMA, assess classification accuracy, and harmonize the SLIs (Table 2.1). The repository further contains the harmonized SLIs in the `spectral_libraries` folder and its subfolders.

Table 2.1. Description of iPython notebooks in MaterialFractionalCover repository.

| File                                   | Description  |
|--|--|
| <code>spectral_unmixing.ipynb</code>   | Example implementation of MESMA.<br>Includes helper functions for data reading, preparation and writing. |
| <code>sl_i_harmonization.ipynb</code>  | Harmonization of SLIs for the Carbon Mapper MFC product.   |
| <code>accuracy_assessment.ipynb</code> | Comparison of a high spatial resolution material classification and simulated Tanager data.              |

### 2.1 Key Dependencies

The Python version used is 3.7.13, Table 2.1.1 lists information about the used packages and the GitHub repository contains a backup of the used conda environment (`conda_environment.yaml`).

The foundation of the algorithm is the MESMA Python package (Crabbé et al. 2020) available on Bitbucket or the Python Package Index. The package is a translation of the original MESMA implementation in the ENVI/IDL VIPER Tools 2.0 package and also offers spectral subsetting/weighting algorithms. A comprehensive documentation and example data are available online (see Table 2.1.1). Other packages used in the iPython notebooks are Spectral Python, numpy, pandas, rasterio, xarray, rioxarray, and scikit-learn. Besides numpy, none of these libraries are requirements for MESMA.

Table 2.1.1. Used python packages.

| Package | Version | Documentation   | Repository  | License     |
|---------|---------|---|---|-------------|
| MESMA   | 1.0.8   | <a href="https://mesma.readthedocs">https://mesma.readthedocs</a> | <a href="https://bitbucket.org/kul-">https://bitbucket.org/kul-</a> | GNU General |

<sup>2</sup> <https://github.com/CMLandOcean/MaterialFractionalCover>

|                 |        |   |   |                                    |
|-----------------|--------|---|---|------------------------------------|
|                 |        | <a href="#">io/</a>   | <a href="#">reseco/mesma/src/master/</a>  | Public License                     |
| Spectral Python | 0.22.4 | <a href="http://www.spectralpython.net/">http://www.spectralpython.net/</a>   | <a href="https://github.com/spectralpython/spectralpython">https://github.com/spectralpython/spectralpython</a> | MIT                                |
| numpy           | 1.21.5 | <a href="https://numpy.org/doc/1.21/index.html">https://numpy.org/doc/1.21/index.html</a>   | <a href="https://github.com/numpy/numpy">https://github.com/numpy/numpy</a>                                     | BSD-3-Clause license               |
| pandas          | 1.3.5  | <a href="https://pandas.pydata.org/pandas-docs/version/1.3/index.html">https://pandas.pydata.org/pandas-docs/version/1.3/index.html</a> | <a href="https://github.com/pandas-dev/pandas">https://github.com/pandas-dev/pandas</a>                         | BSD-3-Clause license               |
| rasterio        | 1.1.0  | <a href="https://rasterio.readthedocs.io/en/latest/index.html">https://rasterio.readthedocs.io/en/latest/index.html</a>                 | <a href="https://github.com/rasterio/rasterio">https://github.com/rasterio/rasterio</a>                         | package - specific license         |
| xarray          | 0.20.1 | <a href="https://docs.xarray.dev/en/stable/">https://docs.xarray.dev/en/stable/</a>   | <a href="https://github.com/pydata/xarray">https://github.com/pydata/xarray</a>                                 | Apache-2.0                         |
| rioxarray       | 0.9.1  | <a href="https://corteva.github.io/rioxarray/html/index.html">https://corteva.github.io/rioxarray/html/index.html</a>                   | <a href="https://github.com/corteva/rioxarray">https://github.com/corteva/rioxarray</a>                         | Unknown, Apache-2.0 licenses found |
| scikit-learn    | 1.0.2  | <a href="https://scikit-learn.org/stable/index.html">https://scikit-learn.org/stable/index.html</a>                                     | <a href="https://github.com/scikit-learn/scikit-learn">https://github.com/scikit-learn/scikit-learn</a>         | BSD-3-Clause license               |

### 2.1.1 Bug Fixing

We identified a bug in the MESMA python package on line 568 in the `mesma` module in the core subpackage, preventing the code from returning a residual image. We changed lines 565 – 568 to the following which solved the issue:

```

565     return (np.reshape(models_expanded.T, (self.n_classes,) + image_dimensions),
566             np.reshape(fractions_expanded.T, (self.n_classes + 1,) + image_dimensions),
567             np.reshape(rmse_expanded, image_dimensions),
568             np.reshape(residuals_expanded, image.shape))

```

## 2.2 Input Data Requirements and Algorithm Constraints

This subsection only describes relevant details to run MESMA. An example data interface is provided in the [spectral\\_unmixing.ipynb](#) iPython notebook. MESMA requires two inputs: 1) a SLI consisting of class labels and corresponding spectra, and 2) an image with the same number of bands as the SLI. The two modules from the MESMA Python package used here are the `mesma` and `hard_classification` modules in the core subpackage.

First, an object of class `MesmaModels` is created using the `MesmaModels()` function from the `mesma` module. Then a look-up-table for all levels of complexity (by default 2-EM and 3-EM) is generated using

the `setup()` function with the class list (np.array of type str) as input. The levels of complexity to be used for MESMA can be controlled with the `select_level()` function. By default MESMA runs 2-EM and 3-EM models but it is also possible to use either one of these and higher levels of complexity can also be initiated as demonstrated in [spectral\\_unmixing.ipynb](#).

To run MESMA, we create an object of class `MesmaCore` using the `MesmaCore()` function from the `mesma` module in the `core` subpackage, and use the `n_cores` parameter to define the number of cores dedicated to the process. Note that parallel processing is implemented through a split of the look-up-table into  $n$  parts defined by the `n_cores` parameter. For each subset of the look-up-table, a separate MESMA instance will be created. Finally, MESMA is executed using the `execute()` function of the `MesmaCore` object. Functions and parameters are described in more detail in Table 2.2.1.

Table 2.2.1.

| Function                 | Parameter                  | Description  | Default                             |
|--------------------------|----------------------------|--|-------------------------------------|
| <code>MesmaCore()</code> | <code>n_cores</code>       | Number of cores dedicated to this process.   | 1                                   |
| <code>execute()</code>   | <code>image</code>         | image to be unmixed, scaled to reflectance, without bad bands, np.array with shape (spatial_x, spatial_y, bands), needs to have the same band setting as library   | NA                                  |
|                          | <code>library</code>       | spectral library as np.array with spectra as columns, scaled to reflectance, without bad bands, needs to have the same band setting as image   | NA                                  |
|                          | <code>look_up_table</code> | dict of all endmember combinations (=models) for MESMA ordered per complexity level and perclass-model ( $n\_models \times n\_endmembers$ ); output of function <code>return_look_up_table()</code> applied to <code>MesmaModels</code> object.    | NA                                  |
|                          | <code>em_per_class</code>  | a dict of all library indices per endmember class; <code>em_per_class</code> attribute of <code>MesmaModels</code> object.   | NA                                  |
|                          | <code>constraints</code>   | A list of length seven: <ol style="list-style-type: none"> <li>1. minimum endmember fraction,</li> <li>2. maximum endmember fraction,</li> <li>3. minimum shade fraction,</li> <li>4. maximum shade fraction,</li> <li>5. maximum RMSE,</li> </ol> | (<br>-0.05,<br>1.05,<br>0.,<br>0.8, |

|  |                        |  |                           |
|--|------------------------|--|---------------------------|
|  |                        | 6. residual reflectance threshold*,<br>7. maximum number of consecutive bands exceeding threshold*<br><br>* set value to -9999 if not used | 0.025, -9999, -9999)      |
|  | no_data_pixels         | tuple of indices of pixels that contain no data (result of np.where), -9999 for GAO VSWIR data   | ()                        |
|  | shade_spectrum         | single spectrum of photometric or non-photometric shade as np.array  | None (=photometric shade) |
|  | fusion_value           | only select a model of higher complexity (e.g. 3-EM over 2-EM) if the RMSE is better with at least this value                              | 0.007                     |
|  | residual_image         | output the residuals as an image (ignored when using band weighing or -selection)  | False                     |
|  | use_band_weighing      | use the weighted linear spectral mixture analysis (Somers et al, 2009)   | False                     |
|  | use_band_selection     | use the bands selection algorithm (Somers et al, 2010)   | False                     |
|  | bands_selection_values | tuple, correlation threshold and decrease for the band selection algorithm   | (0.99, 0.01)              |

## 2.3 Outputs

The `execute()` function returns 3 or 4 arrays of shape (spatial\_x, spatial\_y, bands). 1) The best model where each band represents one class and the values correspond to the respective endmember IDs, 2) the model's fractions where each band contains the fractional cover of the respective class and endmember, plus the fraction of shade, 3) the model's RMSE, and 4) an optional residual image. Output values for unmodeled pixels (according to the constraints) or no data pixels are listed in Table 2.2.2.

Table 2.2.2. Output values for unmodeled or no data pixels.

|                  | Unmodeled pixels | No data pixels |
|------------------|------------------|----------------|
| <b>Models</b>    | -1               | -2             |
| <b>Fractions</b> | 0                | 0              |



|                 |      |      |
|-----------------|------|------|
| RMSE            | 9999 | 9998 |
| Residuals image | 0    | 0    |

## 2.4 Spectral Library Processing and Harmonization

The SLIs briefly described in Section 1.3 are characterized by different band settings and spectral coverage which needed to be aligned with the band setting of the image to be unmixed, and were converted into units of reflectance [-] in the range 0 to 1. We used the `BandResampler()` function from the Spectral Python package available on Github or the Python Package Index to resample the different band settings of the respective SLIs to match GAO and simulated Tanager data (described in Section 3.1).

Further, the classification codes of the SLIs needed to be harmonized to match the proposed material classification code in Table 1.1 (see Appendix and [sli\\_harmonization.ipynb](#) for details). This step is assumed to be a potential source of error because semantic classes may not be translated easily into one another, and endmember spectral signature is not considered for the classification (see Section 1.4). For example, the “Material” attribute *Granite with cement* may be classified as *Natural substrate* or *Concrete*. We further discarded endmembers that did not fit the proposed classification code in Table 1.1 (e.g., lichen, snow, ice).

Table 2.4.1. Publicly available SLIs investigated for their suitability.

| SLI  | Data source   | Spectral range | Description   | Included | License  |
|--|---|----------------|---|----------|--|
| Spectral Library of impervious Urban Materials | <a href="https://zenodo.org/record/4263842">https://zenodo.org/record/4263842</a>   | 400 - 2500 nm  | 74 samples of impervious surfaces   | Yes      | Mozilla Public License 2.0                                     |
| Santa Barbara Urban SLI                        | <a href="https://ecosis.org/package/urban-reflectance-spectra-from-santa-barbara-ca">https://ecosis.org/package/urban-reflectance-spectra-from-santa-barbara-ca</a> | 350 - 2498 nm  | 1065 spectra collected with an ASD around Santa Barbara, California including soil, green vegetation, non-photosynthetic vegetation and various impervious urban surfaces including roofs and paved surfaces. | Yes      | -  |
| ECOSpecLib                                     | <a href="https://speclib.jpl.nasa.gov/">https://speclib.jpl.nasa.gov/</a>   | variable       | > 3400 spectra of natural and man-made materials  | Yes      | ALL RIGHTS RESERVED<br>Copyright<br>California<br>Institute of |

|   |  |                      |  |    |  |
|---|--|----------------------|--|----|--|
|   |  |                      |  |    | Technology<br>U.S.<br>Government<br>Sponsorship<br>Acknowledged<br>under NAS<br>CL#00-1236 |
| Urban Material<br>Spectral<br>Library         | <a href="https://corescholar.libraries.wright.edu/spectral_data/">https://corescholar.libraries.wright.edu/spectral_data/</a>  | 450 - 950 nm         | 60 asphalt,<br>brick/paver spectra   | No | -  |
| Karlsruhe<br>Library of<br>Urban<br>Materials | <a href="https://www.ipf.kit.edu/english/code_1860.php">https://www.ipf.kit.edu/english/code_1860.php</a> ;<br><a href="https://github.com/rebeccailehag/KLUM_library">https://github.com/rebeccailehag/KLUM_library</a> | variable             | 181 urban material<br>samples, 12 material<br>classes, and 33<br>material subclasses   | No | GNU GPLv2  |
| Berlin-Urban-<br>Gradient SLI                 | <a href="https://dataservices.gfz-potsdam.de/en/map/showshort.php?id=escidoc:1823890">https://dataservices.gfz-potsdam.de/en/map/showshort.php?id=escidoc:1823890</a>  | 455.4 - 2446.5<br>nm | 75 artificial and<br>natural surface<br>materials relevant<br>for the study region<br>hierarchically<br>structured into two<br>land cover type<br>levels and a material<br>description | No | Creative<br>Commons<br>Attribution-<br>ShareAlike 4.0<br>International<br>License          |

### 2.2.1 Urban Material Spectral Library

The Urban Material Spectral Library (UMSL; Hossler & Kelsey 2017) consists of 60 asphalt and brick/paver reflectance spectra collected around Dayton, Ohio but only covers the wavelength region between 450 and 950 nm and, therefore, was not considered in the following.

### 2.2.2 Karlsruhe Library of Urban Materials

The Karlsruhe Library of Urban Materials (KLUM; Ilehag et al. 2019) is an urban SLI consisting of field spectra of building materials acquired in Karlsruhe, Germany. The SLI covers the wavelength region from 350 to 2300 nm (water vapor bands around 1000, 1300 and 1800 nm are excluded) and consists of 12 classes and 33 subclasses. Although KLUM is a SLI of urban materials, some of the listed classes (e.g., Granite, Limestone, Sandstone, and Wood) are natural materials and may likewise be listed as *natural substrate*. For most of the KLUM classes, spectral variability is high, and translation into desired material classes may be hampered. For example, all metal spectra either belong to the subclasses painted metal or paint-sprayed metal. Because of the reduced number of bands, we did not use KLUM spectra here.

### 2.2.3 Berlin-Urban-Gradient Spectral Library

The Berlin-Urban-Gradient SLI (BUG; Okujeni et al. 2016) is a dataset for multi-scale unmixing and hard classification analyses of urban environments developed for the EnMAP mission. It consists of 75 natural and artificial surface materials relevant for the study region of Berlin, Germany. All spectra were extracted from airborne imaging spectroscopy data (HyMap, 3.6 m spatial resolution). The SLI covers the wavelength region from 455.4 to 2446.5 nm and is structured in three levels. While “Level 1” and “Level 2” hold information on land use (e.g., *Roof*), “Material name” contains information relevant for this project. Unfortunately, detailed information about the actual physical material is not provided in most cases, and the intended use of the material is described instead. For example, the material description *Brown tile* does not provide information about the actual material (e.g., concrete or metal). Other than this, spectral shape in the wavelength region around 1500 nm appears unnatural in comparison to other SLIs. For these reasons, no endmembers from BUG were used here.

### 2.2.4 Spectral Library of Impervious Urban Materials

The Spectral Library of impervious Urban Materials Version 1.0 (SLUM; Kotthaus 2013; Kotthaus et al. 2014) available from the London Urban Micromet data Archive (LUMA) consists of 74 material samples. Spectra were collected using an SVC HR-1024 field spectrometer and cover the wavelength region from 348.1 to 2505.8 nm. Endmembers are structured in “superclass”, “class”, and “material”. “material”, however, may include conglomerates or mixtures of two or more pure materials with regards to the list in Table 1.1. For example, the sample with the ID G002 has the “class” attribute *Granite* but the “material” is *Granite with concrete*, which itself is a mixture of the proposed material classes “natural substrate” and “concrete” in Table 1.1. Other than this, some metal samples are painted, and it is very likely that the paint pigments define the spectral reflectance, especially in the visible wavelength region. We manually extracted the relevant meta information from the PDF provided in the SLUM repository<sup>3</sup>, then reclassified the SLUM endmembers according to Table 1.1 and stored the new class in the “MaterialClass” attribute (see Appendix and `sl_i_harmonization.ipynb` for details).

### 2.2.5 Santa Barbara Urban Spectral Library

A very comprehensive and extensively used SLI is the Urban SLI from Santa Barbara (UCSB, Herold et al. 2004) available in the Ecological Spectral Information System (EcoSIS<sup>4</sup>). It covers the wavelength region between 400 and 2500 nm and consists of 1065 field spectra measured with an ASD FieldSpec 3 in California. The SLI is structured in 7 levels. The associated attributes, however, often do not match the proposed list of materials in Table 1.1 but rather describe land use type or how a certain type of material has been used.

The UCSB SLI is a single csv file consisting of 1065 spectra structured in 7 levels of which the last one (Level\_7) has all relevant information. We reclassified Level\_7 to match the desired classification according to Table A2.1 and `sl_i_harmonization.ipynb` in the “MaterialClass” attribute.

---

<sup>3</sup> <https://zenodo.org/record/4263842>

<sup>4</sup> <https://ecosis.org/package/urban-reflectance-spectra-from-santa-barbara--ca>

## 2.2.6 ECOSpecLib

Another very comprehensive source is the SLI of the ECOSystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSpecLib<sup>5</sup>; Meerdink et al. 2019) which includes > 3400 spectra of natural and man-made materials. ECOSpecLib includes data from three other libraries (John Hopkins University, Jet Propulsion Laboratory, United States Geological Survey - Reston) and is an update of the ASTER SLI 2.0 (Baldrige et al. 2009).

ECOSpecLib is a collection of text files that had to be translated into a relational database style where each tuple consists of meta data and spectral band attributes. Spectra have been collected with different instruments and therefore have different band settings and varying spectral coverage from the visible to the thermal infrared spectral regions. We first collected all metadata in a single table and selected only those spectra that have at least one band in the wavelength region  $\leq 450$  nm. The resulting subset consists of 1947 spectra. We then excluded all spectra of “type” *Mineral* as there is no corresponding material class in the proposed list (Table 1.1) resulting in a subset of 1090 spectra.

Because the different spectral resolutions and coverages prohibit collection of spectra in a single table, we resampled all spectra to the band setting of GAO or simulated Tanager data before joining spectra with the corresponding metadata based on “Filename” as the key attribute. Based on attributes in different columns we then reclassified the SLI according to Table 1.1 (see Table A3.1) and stored the new class labels in the “MaterialClass” attribute. The corresponding code is provided in the MaterialFractionalCover Github repository in the [SLI\\_preparation.ipynb](#) notebook under the ECOSpecLib headline.

## 2.2.7 Spectral Library Enrichment with GAO VSWIR Data from Phoenix

Running MESMA with default settings and 2-EM models on a high spatial resolution GAO VSWIR subset from Phoenix (see Section 3 for details) revealed that not all pixels could be modeled given the provided constraints and SLI. This can have two reasons: (1) the pure pixel assumption is violated, i.e., more than one class is necessary to unmix a pixel spectrum. This is true even for the high spatial resolution data from Phoenix and may occur particularly along the edges of homogenous areas such as buildings and roads, especially if the adjacent surface is spectrally different, or in areas characterized by a natural spatial variability smaller than the spatial resolution of the data (for example park lawns may be a mixture of PV, NPV and soil), or (2) the SLI does not contain a suitable endmember. To identify the latter, we visually interpreted pixels where the RMSE threshold has been breached and used Google Imagery and Google Street View to identify materials not yet represented in the SLI by adequate endmembers. For each of the materials identified, we manually selected numerous pixels, then visually inspected the within-class spectral variability and split up classes in subclasses if within-class spectral variability was considered too large. For example, the initial class pool was split into 14 subsets representing different spectral shapes of pools. Each class consisted of at least one spectrum, and we used the mean of all spectra per subclass as the final endmember spectrum. Finally, we reclassified the extracted endmembers according to Table 1.1 and ingested them into the compiled SLI; e.g., the 14 pool endmembers representing different pool subclasses were all classified as water.

---

<sup>5</sup> <https://speclib.jpl.nasa.gov/>

### 2.2.8 Harmonization

Although attributes in the original SLIs are different, the prepared tables all contain the attributes “sli\_name” (name of the originating SLI), “MaterialClass” (the semantic class according to Table 1.1), and 428 or 423 band attributes that contain the reflectance per band for the band settings of GAO and simulated Tanager data, respectively. When combining the four SLIs, we preserved the index of the original table in the attribute “original\_index”. (“sli\_name” and “original\_index”) is the combined key that enables reconstructing all available information from the endmember ID in the models output of MESMA.

The final SLIs (GAO\_SLI.csv and Tanager\_SLI.csv in the MaterialFractionalCover Github repository) contain all attributes of the original SLIs, thus, allowing to retrieve all information provided therein including detailed semantic information beyond material class, e.g., retrieving species information from PV endmembers originating from the ECOSpecLib using the “Species” attribute.

Table with example of SLI data headers?

## 3. Example Data Set

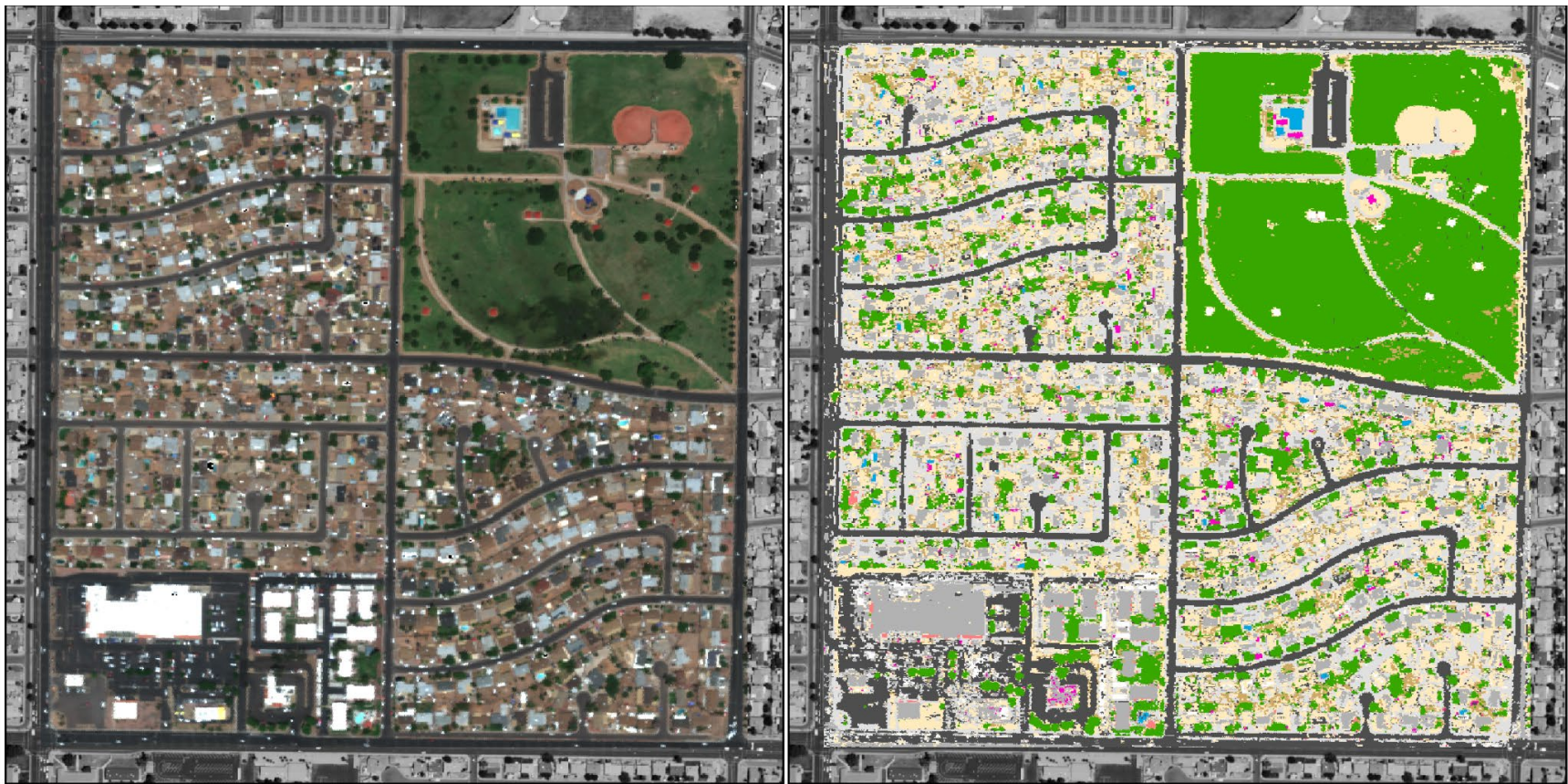
Cities are a mosaic of different materials that may include all the material classes listed in Table 1.1 on small spatial scales and pose a formidable challenge for mapping MFC by means of SMA. On July 16, 2022, GAO mapped approximately 260 km<sup>2</sup> of the city of Phoenix, Arizona. Phoenix is a desert city which impacts the materials used in the urban environment. For example, some materials used for roads and roofs are specifically designed to reduce heat stress. It is, therefore, a good case study to test the applicability of the combined SLI consisting of spectra from different regions of the world.

In addition to testing at full resolution, we also examined the effects of running the MESMA algorithm on the GAO VSWIR data modified to mimic data from the upcoming Tanager sensors. For this, we divided the original rawspace GAO VSWIR data into a grid with an approximate 30m GSD. All IGM pixels within each grid cell were averaged to get a center location for the cell, and when applied across all grid cells this resulted in a 30m IGM. We also applied a gaussian mean filter with  $\sigma = 30.0 / (2 \sqrt{2 \log 2})$  on the radiance pixel values surrounding each IGM pixel center, with weights determined by individual pixel distance from center, resulting in a matching convolved radiance map. Simulated noise was added to this radiance map using the radiometric model provided by Planet Labs PBC, and these data were processed to reflectance using the same methodology as for the full resolution image.

We used the hard classification of MESMA results on 1.05 m spatial resolution GAO VSWIR data for comparison with simulated Tanager data with a spatial resolution of 30 m of the same region. GAO VSWIR data has been atmospherically corrected with ACORN (Atmospheric CORrection Now, Analytical Imaging and Geophysics LLC) and the wavelength regions from 300 to 416 nm, 1300 to 1500 nm, 1790 to 2000 nm, and 2400 to 2600 nm corresponding to telluric water bands or not covered by some endmembers in the SLI were masked in both image and GAO SLI, respectively, resulting in 314 remaining bands. We ran MESMA with 2-EM and 3-EM models and the constraints listed in Table 4.1 using the complete GAO SLI on a 768 × 770 pixel image subset of the Phoenix data set (flightline GAO20220716t191531p0000). We then performed a hard classification on the fractions image (Figure

3.1), i.e., assigned each pixel to the class with the highest fractional coverage, and spatially resampled the classification to the grid of the simulated Tanager data assigning the mode of the classified 1.05 m pixels to the new 30 m pixels (Figure 3.2). The same wavelength mask was applied to the simulated Tanager image and Tanager SLI resulting in 312 remaining bands before we ran MESMA with identical settings (Table 3.1) on the simulated Tanager data from the same region and likewise performed a hard classification (Figure 3.3).





#### Materials

|         |          |                   |                |       |
|---------|----------|-------------------|----------------|-------|
| Asphalt | Concrete | Natural substrate | Other man-made | PV    |
| Brick   | Metal    | NPV               | Plastic        | Water |

Figure 3.1. Example subset from Phoenix data set. Left: Pseudo true-color GAO imagery (1.05 m spatial resolution). Right: Hard classification of 2-EM and 3-EM MESMA fractional cover output. Background: NAIP imagery.





Figure 3.2. Spatial resampling. Left: Hard classification of 2-EM and 3-EM MESMA fractional cover output on 1.05 m spatial resolution GAO data (same as right panel of Figure 3.1). Right: The same hard classification resampled to the grid of simulated Tanager imagery (30 m spatial resolution) using the mode.



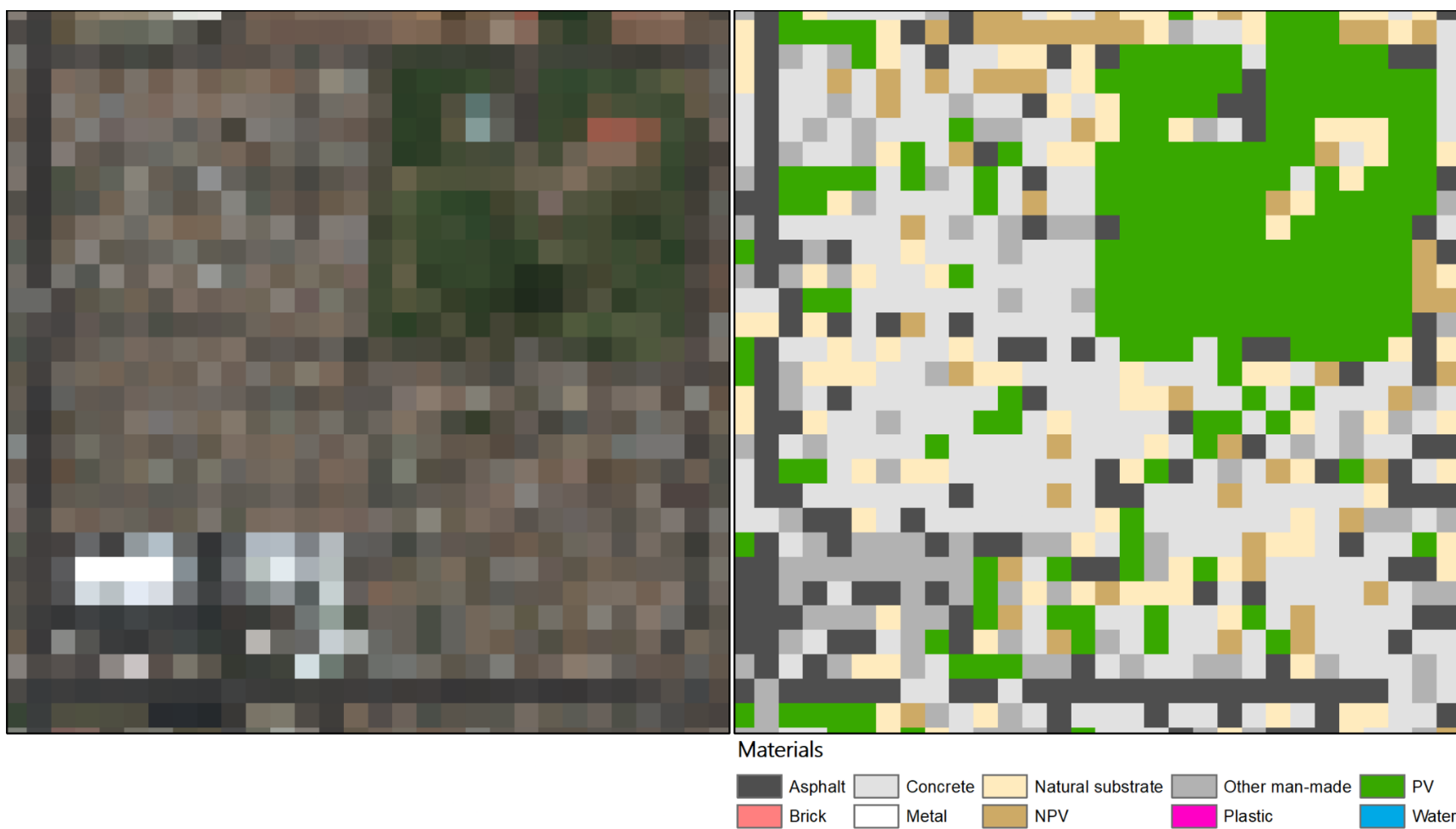


Figure 3.3. Simulated Tanager data for the same image subset from Phoenix. Left: Pseudo true-color simulated Tanager image (30 m spatial resolution). Right: Hard classification of 2-EM and 3-EM MESMA fractional cover output.

Table 3.1. Constraints used for MESMA on the Phoenix data subset (compare Table 2.1.1).

| Constraint                     | Value |
|--------------------------------|-------|
| Minimum endmember fraction     | -0.05 |
| Maximum endmember fraction     | 1.05  |
| Minimum shade fraction         | -0.1  |
| Maximum shade fraction         | 0.8   |
| Residual reflectance threshold | 0.05  |
| Fusion value                   | 0.007 |

## 4. Performance Evaluation

Performance was evaluated by computing precision, recall and f1-score for each of the classes present in the example data subset (see [accuracy\\_assessment.ipynb](#)) by comparing hard classification of the GAO VSWIR MESMA fractional cover output resampled to the grid of the simulated Tanager data using the mode of the classified original 1.05 m pixels inside a 30 m pixel to the hard classification of MESMA fractional cover output from the simulated Tanager data. A visual comparison is provided in Figure 4.1.

Table 4.1. Performance evaluation for example data subset. Classes not identified as dominant at 30 m spatial resolution in either data set are marked with NA.

| MaterialClass     | Precision | Recall | f1-score | Support |
|-------------------|-----------|--------|----------|---------|
| Asphalt           | 0.67      | 0.47   | 0.55     | 177     |
| Brick             | NA        | NA     | NA       | NA      |
| Concrete          | 0.52      | 0.66   | 0.58     | 200     |
| Metal             | 0.00      | 0.00   | 0.00     | 3       |
| Natural substrate | 0.42      | 0.17   | 0.25     | 179     |
| NPV               | 0.02      | 0.25   | 0.04     | 4       |
| Other man-made    | 0.27      | 0.49   | 0.35     | 45      |
| Plastic           | NA        | NA     | NA       | NA      |
| PV                | 0.69      | 0.81   | 0.74     | 175     |
| Water             | 0.00      | 0.00   | 0.00     | 1       |



Figure 4.1. Hard classification comparison. Left: Hard classification of MESMA output on simulated Tanager data (30 m spatial resolution). Right: Hard classification of MESMA output on GAO VSWIR data (1.05 m spatial resolution) resampled to simulated Tanager grid.

# Literature

Baldrige, A. M., Hook, S. J., Grove, C. I., & Rivera, G. (2009). The ASTER spectral library version 2.0. *Remote Sensing of Environment*, 113(4), 711–715. <https://doi.org/10.1016/j.rse.2008.11.007>

Clark, R. N., Swayze, G. A., Livo, K. E., Kokaly, R. F., Sutley, S. J., Dalton, J. B., ... & Gent, C. A. (2003). Imaging spectroscopy: Earth and planetary remote sensing with the USGS Tetracorder and expert systems. *Journal of Geophysical Research: Planets*, 108(E12). <https://doi.org/10.1029/2002JE001847>

Crabbé, A. H., Somers, B., Roberts, D. A., Halligan, K., Dennison, P., Dudley, K. (2020). MESMA QGIS Plugin (Version 1.0.8) [Software]. Available from <https://bitbucket.org/kul-reseco/mesma>.

Herold, M., Roberts, D.A., Gardner, M.E., & Dennison, P.E. (2004). Urban Reflectance Spectra from Santa Barbara, CA. Data set. Available on-line [<http://ecosis.org>] from the Ecological Spectral Information System (EcoSIS)

Hossler, K., & Kelsey, S. (2017). Urban Materials Spectral Library v1.0. [https://corescholar.libraries.wright.edu/spectral\\_data/1](https://corescholar.libraries.wright.edu/spectral_data/1)

Ilebag, R., Schenk, A., Huang, Y., & Hinz, S. (2019). KLUM: An Urban VNIR and SWIR Spectral Library Consisting of Building Materials. *Remote Sensing*, 11(18), 2149. <https://doi.org/10.3390/rs11182149>

Kotthaus, S. (2013). The London Urban Micromet Data Archive (LUMA) Spectral Library of impervious Urban Materials (SLUM). <http://londonclimate.info/LUMA/Conditions.html>

Kotthaus, S., Smith, T. E. L., Wooster, M. J., & Grimmond, C. S. B. (2014). Derivation of an urban materials spectral library through emittance and reflectance spectroscopy. *ISPRS Journal of Photogrammetry and Remote Sensing*, 94, 194–212. <https://doi.org/10.1016/j.isprsjprs.2014.05.005>

Loughlin, C., Pieper, M., Manolakis, D., Bostick, R., Weisner, A., & Cooley, T. (2020). Efficient Hyperspectral Target Detection and Identification with Large Spectral Libraries. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 6019–6028. <https://doi.org/10.1109/JSTARS.2020.3027155>

Meerdink, S. K., Hook, S. J., Roberts, D. A., & Abbott, E. A. (2019). The ECOSTRESS spectral library version 1.0. *Remote Sensing of Environment*, 230 (March), 111196. <https://doi.org/10.1016/j.rse.2019.05.015>

Myint, S. W., & Okin, G. S. (2009). Modelling land-cover types using multiple endmember spectral mixture analysis in a desert city. *International Journal of Remote Sensing*, 30(9), 2237–2257. <https://doi.org/10.1080/01431160802549328>

Okujeni, A.; van der Linden, S.; Hostert, P. (2016): Berlin-Urban-Gradient dataset 2009 - An EnMAP Preparatory Flight Campaign (Datasets). V. 1.2. GFZ Data Services.  
<http://doi.org/10.5880/enmap.2016.008>.

Peterson, S. H., Roberts, D. A., Beland, M., Kokaly, R. F., & Ustin, S. L. (2015). Oil detection in the coastal marshes of Louisiana using MESMA applied to band subsets of AVIRIS data. *Remote Sensing of Environment*, 159, 222–231. <https://doi.org/10.1016/j.rse.2014.12.009>

Roberts, D. A., Gardner, M., Church, R., Ustin, S., Scheer, G., & Green, R. O. (1998). Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing of Environment*, 65(3), 267–279. [https://doi.org/10.1016/S0034-4257\(98\)00037-6](https://doi.org/10.1016/S0034-4257(98)00037-6)

Roth, K. L., Roberts, D. A., Dennison, P. E., Alonzo, M., Peterson, S. H., & Beland, M. (2015). Differentiating plant species within and across diverse ecosystems with imaging spectroscopy. *Remote Sensing of Environment*, 167, 135–151. <https://doi.org/10.1016/j.rse.2015.05.007>

Somers, B., Delalieux, S., Stuckens, J., Verstraeten, W. W., & Coppin, P. (2009). A weighted linear spectral mixture analysis approach to address endmember variability in agricultural production systems. *International Journal of Remote Sensing*, 30(1), 139–147. <https://doi.org/10.1080/01431160802304625>

Somers, B., Delalieux, S., Verstraeten, W. W., van Aardt, J. A. N., Albrigo, G. L., & Coppin, P. (2010). An automated waveband selection technique for optimized hyperspectral mixture analysis. *International Journal of Remote Sensing*, 31(20), 5549–5568. <https://doi.org/10.1080/01431160903311305>

Wetherley, E. B., Roberts, D. A., & McFadden, J. P. (2017). Mapping spectrally similar urban materials at sub-pixel scales. *Remote Sensing of Environment*, 195, 170–183.  
<https://doi.org/10.1016/j.rse.2017.04.013>

Yackel, J. J., Nandan, V., Mahmud, M., Scharien, R., Kang, J. W., & Geldsetzer, T. (2017). A spectral mixture analysis approach to quantify Arctic first-year sea ice melt pond fraction using QuickBird and MODIS reflectance data. *Remote Sensing of Environment*, 204(September), 704–716.  
<https://doi.org/10.1016/j.rse.2017.09.030>

Youngentob, K. N., Roberts, D. A., Held, A. A., Dennison, P. E., Jia, X., & Lindenmayer, D. B. (2011). Mapping two Eucalyptus subgenera using multiple endmember spectral mixture analysis and continuum-removed imaging spectrometry data. *Remote Sensing of Environment*, 115(5), 1115–1128.  
<https://doi.org/10.1016/j.rse.2010.12.012>

# Appendix

## A1 Spectral Library of Impervious Urban Materials

Table A1.1. Classification scheme of SLUM SLI (columns 1-3) and newly assigned material.

| Superclass      | Class                  | Material                                     | Newly assigned material |
|-----------------|------------------------|--|-------------------------|
| Asphalt         | Asphalt roofing        | Asphalt roofing shingle with slate chippings | Asphalt                 |
|                 | Road asphalt           | Asphalt with stone aggregate                 | Asphalt                 |
|                 |                        | Tarmac                                       | Asphalt                 |
| Brick           | Cement brick           | Cement                                       | Concrete                |
|                 | Ceramic brick          | Ceramic                                      | Brick                   |
|                 |                        | Ceramic brick                                | Brick                   |
|                 |                        | Ceramic brick with cement                    | Other man-made          |
|                 |                        | Ceramic brick with paint                     | Other man-made          |
|                 |                        | Ceramic with cement                          | Other man-made          |
|                 |                        | Ceramic with paint                           | Other man-made          |
| Concrete/Cement | Cement                 | Cement                                       | Concrete                |
|                 | Concrete               | Concrete                                     | Concrete                |
|                 |                        | Concrete with small aggregate                | Concrete                |
|                 |                        | Concrete with small stone aggregate          | Concrete                |
| Granite         | Granite                | Granite                                      | Natural substrate       |
|                 |                        | Granite with cement                          | Other man-made          |
| Metal           | Metal                  | Aluminium                                    | Metal                   |
|                 |                        | Aluminium plus zinc                          | Metal                   |
|                 |                        | Aluminium, stucco                            | Metal                   |
|                 |                        | Iron   | Metal                   |
|                 |                        | Lead   | Metal                   |
|                 |                        | Metal with paint                             | Metal                   |
| PVC             | PVC roofing sheet      | PVC  | Plastic                 |
| Quartzite       | Quartzite conglomerate | Quartzite                                    | Natural substrate       |
| Shingle         | Roofing shingle        | Fibre cement                                 | Concrete                |
|                 |                        | Slate  | Natural substrate       |
|                 |                        | Slate roofing shingle                        | Natural substrate       |
| Stone           | Stone                  | Carboniferous coral                          | Natural substrate       |

|      |              |           |                   |
|------|--------------|-----------|-------------------|
|      |              | limestone |                   |
|      |              | Limestone | Natural substrate |
|      |              | Sandstone | Natural substrate |
| Tile | Roofing tile | Cement    | Concrete          |
|      |              | Ceramic   | Other man-made    |

## A2 Santa Barbara Urban Spectral Library

Table A2.2. Level\_7 classification scheme of UCSB SLI and newly assigned material.

| Level_7              | Newly assigned material |
|----------------------|-------------------------|
| ANNUAL_FORB          | PV                      |
| ASPHALT_GRAVEL       | Asphalt                 |
| ASPHALT_PARKING_LOT  | Asphalt                 |
| ASPHALT_ROAD         | Asphalt                 |
| ASPHALT_ROOF         | Asphalt                 |
| BARK                 | NPV                     |
| BOUGAINVILLEA        | PB                      |
| BRICK                | Brick                   |
| BRICK_SIDEWALK       | Brick                   |
| COMP_SHINGLE_ROOF    | Other man-made          |
| CONCRETE_BRIDGE      | Concrete                |
| CONCRETE_GRAVEL      | Concrete                |
| CONCRETE_PARKING_LOT | Concrete                |
| CONCRETE_ROAD        | Concrete                |
| CONCRETE_SIDEWALK    | Concrete                |
| CONCRETE_TILE_ROOF   | Concrete                |
| ENGLISH_IVY          | PV                      |
| GLASS_ROOF           | Other man-made          |

|                   |                   |
|-------------------|-------------------|
| GRAVEL            | Natural substrate |
| GRAVEL_ROOF       | Natural substrate |
| IRGR              | PV                |
| LICHEN            | <i>EXCLUDED</i>   |
| METAL_MANHOLE     | Metal             |
| METAL_ROOF        | Metal             |
| MIRRA             | PV                |
| NPV               | NPV               |
| PAINT             | Other man-made    |
| PAINTED_ROOF      | Other man-made    |
| PALM              | PV                |
| SAND              | Natural substrate |
| SOIL              | Natural substrate |
| STAR_JASMINE      | PV                |
| TILE_ROAD         | Other man-made    |
| TILE_ROOF         | Other man-made    |
| WOOD              | NPV               |
| WOOD_SHINGLE_ROOF | NPV               |

## A3 ECOSTRESS

Table A3.3. Classification scheme of ECOSTRESS SLI (columns 1-4) and newly assigned material.

| Type    | Class    | Subclass              | Name                  | Newly assigned Material |
|---------|----------|-----------------------|-----------------------|-------------------------|
| Manmade | Concrete | Construction Concrete | Construction Concrete | Concrete                |
|         |          | Paving Concrete       | Asphaltic concrete    | Concrete                |
|         |          |                       | Construction          | Concrete                |



|  |                               |                    |                                 |                |
|--|-------------------------------|--------------------|---------------------------------|----------------|
|  |                               |                    | Concrete                        |                |
|  |                               |                    | Construction Concrete           | Concrete       |
|  | General Construction Material | Brick              | Bare Red Brick                  | Brick          |
|  |                               |                    | Red smooth-faced Brick          | Brick          |
|  |                               |                    | Weathered Red Brick             | Brick          |
|  |                               | Cement Cinderblock | Construction Concrete           | Concrete       |
|  |                               | Cinder             | Cinders, ashen                  | Other man-made |
|  |                               | Glas               | Plate Window Glass              | Other man-made |
|  |                               | Marble             | White Marble                    | Other man-made |
|  |                               | Paint              | Black gloss paint               | Other man-made |
|  |                               |                    | Black paint                     | Other man-made |
|  |                               |                    | Olive green gloss paint         | Other man-made |
|  |                               |                    | Olive green paint               | Other man-made |
|  |                               | Wood               | Pine Wood                       | NPV            |
|  | Road                          | Paving Asphalt     | Construction Asphalt            | Asphalt        |
|  |                               | Tar                | Construction Tar                | Asphalt        |
|  | Roofing Material              | Metal              | Aluminum Metal                  | Metal          |
|  |                               |                    | Copper Metal                    | Metal          |
|  |                               |                    | Galvanized Steel Metal          | Metal          |
|  |                               |                    | Oxidized Galvanized Steel Metal | Metal          |

|     |      |                 |                                     |                   |
|-----|------|-----------------|-------------------------------------|-------------------|
|     |      | Roofing Paper   | Black tar paper                     | Other man-made    |
|     |      | Roofing Shingle | Asphalt Shingle                     | Asphalt           |
|     |      | Rubber          | Black unspecified rubber            | Other man-made    |
|     |      |                 | White fiberglass unspecified rubber | Other man-made    |
|     |      |                 | White rubberized coating            | Other man-made    |
|     |      | Shingle         | Asphalt roofing shingle             | Asphalt           |
|     |      |                 | Reddish Asphalt roofing shingle     | Asphalt           |
|     |      |                 | Reddish asphalt Shingle             | Asphalt           |
|     |      |                 | Slate stone Shingle                 | Natural substrate |
|     |      | Tile            | Terra cotta Tiles                   | Brick             |
| NPV | Bark | Tile            | Abies concolor bark                 | NPV               |
|     |      |                 | Acer rubrum                         | NPV               |
|     |      |                 | Betula papyrifera                   | NPV               |
|     |      |                 | Calocedrus decurrens bark           | NPV               |
|     |      |                 | Pinus coulteri bark                 | NPV               |
|     |      |                 | Pinus lambertiana bark              | NPV               |
|     |      |                 | Pinus ponderosa Bark                | NPV               |
|     |      |                 | Pinus ponderosa bark                | NPV               |
|     |      |                 | Pinus strobus                       | NPV               |
|     |      |                 | Quercus rubra                       | NPV               |

|    |          |              |                                       |                 |
|----|----------|--------------|---------------------------------------|-----------------|
|    | Branches | Tile         | Adenostoma fasciculatum branch        | NPV             |
|    |          |              | Ceanothus megacarpus branch           | NPV             |
|    |          |              | Foeniculum vulgare litter             | NPV             |
|    |          |              | Salvia leucophylla 1                  | NPV             |
|    |          |              | Salvia leucophylla 2                  | NPV             |
|    |          |              | Salvia leucophylla 3                  | NPV             |
|    | Flowers  | Tile         | Calocedrus decruens                   | NPV             |
|    | Leaves   | Tile         | Avena fatua litter                    | NPV             |
|    |          |              | Dry grass                             | NPV             |
|    |          |              | Misc Grass Litter                     | NPV             |
|    |          |              | Misc Grass Litter - Mostly decomposed | NPV             |
|    |          |              | Misc Leaf Litter                      | NPV             |
|    |          |              | Quercus sp. litter                    | NPV             |
|    | Lichen   | Tile         | dry brown lichen                      | <i>EXCLUDED</i> |
|    |          |              | lichen off trees                      | <i>EXCLUDED</i> |
|    | Needles  | Tile         | Abies concolor dry needles            | NPV             |
|    |          |              | Pinus coulteri dry needles            | NPV             |
|    |          |              | Pinus lambertiana dry needles         | NPV             |
|    |          |              | Pinus ponderosa dry needles           | NPV             |
| PV | Grass    | Chromoxerert | Avena fatua                           | PV              |

|  |       |              |                             |    |
|--|-------|--------------|-----------------------------|----|
|  |       |              | Bromus diandrus             | PV |
|  |       |              | Grass                       | PV |
|  | Shrub | Chromoxerert | Adenostoma fasciculatum 1   | PV |
|  |       |              | Adenostoma fasciculatum 2   | PV |
|  |       |              | Adenostoma fasciculatum 3   | PV |
|  |       |              | Agave attenuata             | PV |
|  |       |              | Aloe arborescens            | PV |
|  |       |              | Aloe arborescens flower     | PV |
|  |       |              | Arctostaphylos glandulosa 1 | PV |
|  |       |              | Arctostaphylos glandulosa 2 | PV |
|  |       |              | Arctostaphylos glandulosa 3 | PV |
|  |       |              | Baccharis pilularis 1       | PV |
|  |       |              | Baccharis pilularis 2       | PV |
|  |       |              | Baccharis pilularis 3       | PV |
|  |       |              | Ceanothus megacarpus 1      | PV |
|  |       |              | Ceanothus megacarpus 2      | PV |
|  |       |              | Ceanothus megacarpus 3      | PV |
|  |       |              | Ceanothus spinosus 1        | PV |
|  |       |              | Ceanothus spinosus 2        | PV |

|  |      |              |                               |    |
|--|------|--------------|-------------------------------|----|
|  |      |              | Ceanothus spinosus 3          | PV |
|  |      |              | Gasteria acinacifolia         | PV |
|  |      |              | Heteromeles arbutifolia 1     | PV |
|  |      |              | Heteromeles arbutifolia 2     | PV |
|  |      |              | Heteromeles arbutifolia 3     | PV |
|  |      |              | Juniperus chinensis           | PV |
|  |      |              | Portulacaria afra             | PV |
|  |      |              | Portulacaria afra 'Low Form'  | PV |
|  |      |              | Portulacaria afra 'Variegata' | PV |
|  |      |              | Puya venusta                  | PV |
|  |      |              | Salvia leucophylla 1          | PV |
|  |      |              | Salvia leucophylla 2          | PV |
|  |      |              | Salvia leucophylla 3          | PV |
|  |      |              | Umbellularia californica 1    | PV |
|  |      |              | Umbellularia californica 2    | PV |
|  |      |              | Umbellularia californica 3    | PV |
|  |      | Tile         | Arctostaphylos glandulosa 4   | PV |
|  |      |              | Arctostaphylos glandulosa 5   | PV |
|  | Tree | Chromoxerert | Abies concolor 1              | PV |

|  |  |  |                           |    |
|--|--|--|---------------------------|----|
|  |  |  | Abies concolor 2          | PV |
|  |  |  | Abies concolor 3          | PV |
|  |  |  | Acacia caven              | PV |
|  |  |  | Acacia visco              | PV |
|  |  |  | Acer paxii                | PV |
|  |  |  | Acer pensylvanicum        | PV |
|  |  |  | Acer rubrum               | PV |
|  |  |  | Aloe bainesii             | PV |
|  |  |  | Bambusa<br>beeheyana      | PV |
|  |  |  | Bambusa tuldoidea         | PV |
|  |  |  | Beaucarnea<br>recurvata   | PV |
|  |  |  | Betula lenta              | PV |
|  |  |  | Betula papyrifera         | PV |
|  |  |  | Brachychiton<br>discolor  | PV |
|  |  |  | Brachychiton<br>rupestris | PV |
|  |  |  | Caesalpinia cacalaco      | PV |
|  |  |  | Caesalpinia<br>cacalaco   | PV |
|  |  |  | Calocedrus<br>decruens 1  | PV |
|  |  |  | Calocedrus<br>decruens 2  | PV |
|  |  |  | Calocedrus<br>decruens 3  | PV |
|  |  |  | Calodendrum               | PV |

|  |  |  |                                   |    |
|--|--|--|-----------------------------------|----|
|  |  |  | capense                           |    |
|  |  |  | Casimiroa edulis                  | PV |
|  |  |  | Cassia leptophylla                | PV |
|  |  |  | Cedrus atlantica                  | PV |
|  |  |  | Cedrus atlantica<br>'glauca'      | PV |
|  |  |  | Cedrus deodara                    | PV |
|  |  |  | Cercidium<br>pennisulare          | PV |
|  |  |  | Chorisia insignis                 | PV |
|  |  |  | Chorisia speciosa                 | PV |
|  |  |  | Citharexylum<br>montevidense      | PV |
|  |  |  | Conifer                           | PV |
|  |  |  | Deciduous                         | PV |
|  |  |  | Ehretia austin-<br>smithii        | PV |
|  |  |  | Eucalyptus ficifolia              | PV |
|  |  |  | Eucalyptus<br>kartzoffiana        | PV |
|  |  |  | Eucalyptus<br>maculata            | PV |
|  |  |  | Eucalyptus rudis                  | PV |
|  |  |  | Eucalyptus rudius                 | PV |
|  |  |  | Eucalyptus saligna                | PV |
|  |  |  | Fagus grandifolia                 | PV |
|  |  |  | Fagus sylvatica<br>'atropurpurea' | PV |

|  |  |  |                                 |    |
|--|--|--|---------------------------------|----|
|  |  |  | Ficus craterostoma              | PV |
|  |  |  | Ficus macrophylla f. columnaris | PV |
|  |  |  | Ficus platypoda                 | PV |
|  |  |  | Ficus socotrana                 | PV |
|  |  |  | Ficus thonningii                | PV |
|  |  |  | Ginkgo biloba                   | PV |
|  |  |  | Ginkgo biloba                   | PV |
|  |  |  | Hetrosideros excelsa            | PV |
|  |  |  | Jacaranda mimosifolia           | PV |
|  |  |  | Lagerstroemia indica            | PV |
|  |  |  | Macadamia integrifolia          | PV |
|  |  |  | Magnolia grandiflora            | PV |
|  |  |  | Melaleuca linariifolia          | PV |
|  |  |  | Melaleuca lanceolata            | PV |
|  |  |  | Metrosideros excelsa            | PV |
|  |  |  | Olea africana                   | PV |
|  |  |  | Ombu tree                       | PV |
|  |  |  | Peltophorum africanum           | PV |
|  |  |  | Peltophorum dubium              | PV |



|  |  |                         |    |
|--|--|-------------------------|----|
|  |  | Phyllostachys aurea     | PV |
|  |  | Phyllostachys vivax     | PV |
|  |  | Phytolacca dioica       | PV |
|  |  | Pinus lambertiana 1     | PV |
|  |  | Pinus lambertiana 2     | PV |
|  |  | Pinus lambertiana 3     | PV |
|  |  | Pinus ponderosa 1       | PV |
|  |  | Pinus ponderosa 2       | PV |
|  |  | Pinus ponderosa 3       | PV |
|  |  | Pinus strobus           | PV |
|  |  | Podocarpus<br>gracilior | PV |
|  |  | Prosopis articulata     | PV |
|  |  | Prunus serotina         | PV |
|  |  | Pylostachys vivax       | PV |
|  |  | Quercus agrifolia       | PV |
|  |  | Quercus agrifolia 1     | PV |
|  |  | Quercus agrifolia 2     | PV |
|  |  | Quercus agrifolia 3     | PV |
|  |  | Quercus douglasii 1     | PV |
|  |  | Quercus douglasii 2     | PV |
|  |  | Quercus douglasii 3     | PV |
|  |  | Quercus ilex            | PV |
|  |  | Quercus lobata 1        | PV |
|  |  | Quercus lobata 2        | PV |

|      |         |         |                            |                   |
|------|---------|---------|----------------------------|-------------------|
|      |         |         | Quercus lobata 3           | PV                |
|      |         |         | Quercus robur              | PV                |
|      |         |         | Quercus rubra              | PV                |
|      |         |         | Quercus suber              | PV                |
|      |         |         | Quercus virginana          | PV                |
|      |         |         | Rubus occidentalis         | PV                |
|      |         |         | Salix babylonica           | PV                |
|      |         |         | Taxodium mucronatum        | PV                |
|      |         |         | Tipuana tipu               | PV                |
|      |         |         | Tsuga canadensis           | PV                |
|      |         |         | Uvularia sessifolia        | PV                |
| Rock | Igneous | Alkalic | Hornblende Syenite         | Natural substrate |
|      |         |         | Nepheline-Sodalite Syenite | Natural substrate |
|      |         |         | Syenite                    | Natural substrate |
|      |         |         | Trachyte                   | Natural substrate |
|      |         | Basic   | Amygdaloidal Basalt        | Natural substrate |
|      |         |         | Scoria                     | Natural substrate |
|      |         | Felsic  | Alkali Granite             | Natural substrate |
|      |         |         | Alkalic Granite            | Natural substrate |
|      |         |         | Altered volcanic tuff      | Natural substrate |
|      |         |         | Aplite                     | Natural substrate |
|      |         |         | Aporhyolite (felsite)      | Natural substrate |
|      |         |         | Biotite Granite            | Natural substrate |

|  |  |              |                             |                   |
|--|--|--------------|-----------------------------|-------------------|
|  |  |              | Granite                     | Natural substrate |
|  |  |              | Hornblende Granite          | Natural substrate |
|  |  |              | Muscovite-Biotite Granite   | Natural substrate |
|  |  |              | Obsidian                    | Natural substrate |
|  |  |              | Pegmatite                   | Natural substrate |
|  |  |              | Quartz Felsite Porphyry     | Natural substrate |
|  |  |              | Rhyolite                    | Natural substrate |
|  |  |              | Tuff                        | Natural substrate |
|  |  | Feslic       | Rhyolite Porphyry           | Natural substrate |
|  |  | Intermediate | Alkalic Syenite             | Natural substrate |
|  |  |              | Andesite Breccia            | Natural substrate |
|  |  |              | Andesite Porphyry           | Natural substrate |
|  |  |              | Augite-hypersthene Andesite | Natural substrate |
|  |  |              | Basaltic Andesite           | Natural substrate |
|  |  |              | Diorite                     | Natural substrate |
|  |  |              | Diorite Porphyry            | Natural substrate |
|  |  |              | Granodiorite                | Natural substrate |
|  |  |              | Mica Dacite Porphyry        | Natural substrate |
|  |  |              | Monzonite                   | Natural substrate |
|  |  |              | Nepheline Syenite           | Natural substrate |
|  |  |              | Quartz Monzonite            | Natural substrate |
|  |  |              | Quartz Monzonite Porphyry   | Natural substrate |

|  |  |            |                             |                   |
|--|--|------------|-----------------------------|-------------------|
|  |  |            | Rhyolitic obsidian          | Natural substrate |
|  |  |            | Tonalite (Bonsall Tonalite) | Natural substrate |
|  |  | Mafic      | Alkali Basalt               | Natural substrate |
|  |  |            | Anorthosite                 | Natural substrate |
|  |  |            | Basalt                      | Natural substrate |
|  |  |            | Basanite                    | Natural substrate |
|  |  |            | Diabase                     | Natural substrate |
|  |  |            | Diabase Porphyry            | Natural substrate |
|  |  |            | Gabbro                      | Natural substrate |
|  |  |            | Hypersthene Gabbro          | Natural substrate |
|  |  |            | Hypersthene Gabbro (Norite) | Natural substrate |
|  |  |            | Lamprophyre                 | Natural substrate |
|  |  |            | Norite                      | Natural substrate |
|  |  |            | Olivine Basalt Porphyry     | Natural substrate |
|  |  |            | Olivine Gabbro              | Natural substrate |
|  |  |            | Unaltered volcanic tuff     | Natural substrate |
|  |  |            | Vesicular Basalt            | Natural substrate |
|  |  | Ultramafic | Augite-Mica Peridotite      | Natural substrate |
|  |  |            | Dunite                      | Natural substrate |
|  |  |            | Dunite (Olivine Peridotite) | Natural substrate |
|  |  |            | Ijolite                     | Natural substrate |

|  |              |         |                           |                   |
|--|--------------|---------|---------------------------|-------------------|
|  |              |         | Mica Peridotite           | Natural substrate |
|  |              |         | Picrite                   | Natural substrate |
|  |              |         | Pyroxenite                | Natural substrate |
|  | Intermediate | Felsic  | Dacite                    | Natural substrate |
|  | Metamorphic  | Gneiss  | Albite Gneiss             | Natural substrate |
|  |              |         | Augen Gneiss              | Natural substrate |
|  |              |         | Biotite Gneiss            | Natural substrate |
|  |              |         | Chloritic Gneiss          | Natural substrate |
|  |              |         | Diorite Gneiss            | Natural substrate |
|  |              |         | Felsitic Gneiss           | Natural substrate |
|  |              |         | Garnet Gneiss             | Natural substrate |
|  |              |         | Granitoid Gneiss          | Natural substrate |
|  |              |         | Hornblende Gneiss         | Natural substrate |
|  |              |         | Sillimanite-Garnet Gneiss | Natural substrate |
|  |              |         | Syenite Gneiss            | Natural substrate |
|  |              | Hornfel | Banded Hornfels           | Natural substrate |
|  |              |         | Hornfels                  | Natural substrate |
|  |              |         | Spotted Hornfels          | Natural substrate |
|  |              | Marble  | Dolomite Marble           | Natural substrate |
|  |              |         | Dolomitic Marble          | Natural substrate |
|  |              |         | Marble                    | Natural substrate |
|  |              |         | Pink Marble               | Natural substrate |
|  |              |         | Serpentine Marble         | Natural substrate |
|  |              |         | Verde Antique             | Natural substrate |

|  |  |              |                           |                   |
|--|--|--------------|---------------------------|-------------------|
|  |  |              | White Marble              | Natural substrate |
|  |  | Phyllite     | Phyllite                  | Natural substrate |
|  |  | Quartzite    | Gray Quartzite            | Natural substrate |
|  |  |              | Green Quartzite           | Natural substrate |
|  |  |              | Pink Quartzite            | Natural substrate |
|  |  |              | Purple Quartzite          | Natural substrate |
|  |  |              | Quartzite                 | Natural substrate |
|  |  |              | Red Quartzite             | Natural substrate |
|  |  | Schist       | Anthophyllite Mica Schist | Natural substrate |
|  |  |              | Biotite Schist            | Natural substrate |
|  |  |              | Chlorite Schist           | Natural substrate |
|  |  |              | Garnetiferous Mica Schist | Natural substrate |
|  |  |              | Graphite Schist           | Natural substrate |
|  |  |              | Green Schist              | Natural substrate |
|  |  |              | Hornblende Schist         | Natural substrate |
|  |  |              | Mica Schist               | Natural substrate |
|  |  |              | Quartz-Sericite Schist    | Natural substrate |
|  |  |              | Tourmaline Schist         | Natural substrate |
|  |  |              | Tourmaline-Mica Schist    | Natural substrate |
|  |  |              | Tremolite Schist          | Natural substrate |
|  |  | Serpentinite | Serpentine                | Natural substrate |
|  |  | Slate        | Chiastolic Slate          | Natural substrate |
|  |  |              | Gray Slate                | Natural substrate |

|  |             |                      |                                     |                   |
|--|-------------|----------------------|-------------------------------------|-------------------|
|  |             |                      | Green Slate                         | Natural substrate |
|  |             |                      | Red Slate                           | Natural substrate |
|  | Sedimentary | Breccia              | Limestone Breccia                   | Natural substrate |
|  |             | Chemical precipitate | Gypsum                              | Natural substrate |
|  |             |                      | Oolitic Iron Ore                    | Natural substrate |
|  |             | Conglomerate         | Limestone Conglomerate-Breccia      | Natural substrate |
|  |             |                      | Quartz Conglomerate                 | Natural substrate |
|  |             | Dolomite             | Dolomite<br>CaMgCO <sub>3</sub>     | Natural substrate |
|  |             | Limestone            | Argillaceous Limestone              | Natural substrate |
|  |             |                      | Chalk                               | Natural substrate |
|  |             |                      | Cherty Limestone                    | Natural substrate |
|  |             |                      | Chocolate "Marble" Limestone        | Natural substrate |
|  |             |                      | Dolomitic Limestone                 | Natural substrate |
|  |             |                      | Ecrinal Limestone                   | Natural substrate |
|  |             |                      | Fossiliferous Limestone             | Natural substrate |
|  |             |                      | Gray Limestone (Birdseye Limestone) | Natural substrate |
|  |             |                      | Limestone                           | Natural substrate |
|  |             |                      | Limestone CaCO <sub>3</sub>         | Natural substrate |
|  |             |                      | Lithographic Limestone              | Natural substrate |

|  |  |           |                                     |                   |
|--|--|-----------|-------------------------------------|-------------------|
|  |  |           | Oolitic Limestone                   | Natural substrate |
|  |  |           | Travertine<br>(Calcareous Tufa)     | Natural substrate |
|  |  | Sandstone | Argillaceous Sandstone              | Natural substrate |
|  |  |           | Arkose                              | Natural substrate |
|  |  |           | Arkosic Sandstone                   | Natural substrate |
|  |  |           | Ferruginous Sandstone               | Natural substrate |
|  |  |           | Glaucinitic Sandstone               | Natural substrate |
|  |  |           | Gray Sandstone                      | Natural substrate |
|  |  |           | Greywacke Sandstone                 | Natural substrate |
|  |  |           | Micaceous Sandstone<br>(Brownstone) | Natural substrate |
|  |  |           | Purple-banded Sandstone             | Natural substrate |
|  |  |           | Red Sandstone                       | Natural substrate |
|  |  |           | Sandstone<br>(Flagstone)            | Natural substrate |
|  |  |           | Sandstone<br>(Micaceous Red)        | Natural substrate |
|  |  |           | Sandstone (Red)                     | Natural substrate |
|  |  | Shale     | Arenaceous Shale                    | Natural substrate |
|  |  |           | Argillaceous Shale                  | Natural substrate |
|  |  |           | Black Shale                         | Natural substrate |
|  |  |           | Calcareous Shale                    | Natural substrate |
|  |  |           | Carbonaceous Shale                  | Natural substrate |



|      |         |             |                                    |                   |
|------|---------|-------------|------------------------------------|-------------------|
|      |         |             | Illite-bearing Shale               | Natural substrate |
|      |         |             | Oil Shale (Kerogen Shale)          | Natural substrate |
|      |         |             | Phosphorite                        | Natural substrate |
|      |         |             | Shale (Arenaceous)                 | Natural substrate |
|      |         |             | Shale (Calcareous)                 | Natural substrate |
|      |         |             | Shale (Phosphatic)                 | Natural substrate |
|      |         | Siliceou    | Diatomaceous Earth                 | Natural substrate |
|      |         |             | Siliceous Oolite                   | Natural substrate |
|      |         | Siltstone   | Limestone Siltstone                | Natural substrate |
|      |         |             | Limestone-Siltstone                | Natural substrate |
|      |         |             | Siltstone                          | Natural substrate |
|      |         | Travertine  | Travertine                         | Natural substrate |
|      |         | dolomite    | Dolomite<br>CaMgCO <sub>3</sub>    | Natural substrate |
| Soil | Alfisol | Fragiboralf | Pale brown silty loam              | Natural substrate |
|      |         | Haploxeralf | Brown to dark brown gravelly loam  | Natural substrate |
|      |         | Haplustalf  | Brown fine sandy loam              | Natural substrate |
|      |         |             | Brown loamy fine sand              | Natural substrate |
|      |         | Paleustalf  | Brown sandy loam                   | Natural substrate |
|      |         |             | Dark reddish brown fine sandy loam | Natural substrate |
|      |         |             | Reddish brown fine sandy loam      | Natural substrate |
|      |         |             |                                    |                   |

|  |            |                 |  |                   |
|--|------------|-----------------|--|-------------------|
|  | Aridisol   | Calciorthid     | Light yellowish brown interior dry gravelly loam                   | Natural substrate |
|  |            |                 | Light yellowish brown loam   | Natural substrate |
|  |            | Camborthid      | Brown silty loam   | Natural substrate |
|  |            |                 | Light yellowish brown loamy sand                                   | Natural substrate |
|  |            | Gypsiorthid     | Very pale brown to brownish yellow interior dry gravelly silt loam | Natural substrate |
|  |            | Haplargid       | Brown gravelly sandy loam  | Natural substrate |
|  |            | Salorthid       | Dark brown interior moist clay loam                                | Natural substrate |
|  |            |                 | Dark yellowish brown silty clay                                    | Natural substrate |
|  |            |                 | Light yellowish brown clay   | Natural substrate |
|  |            | Torripsamment   | Very dark grayish brown loamy sand                                 | Natural substrate |
|  | Entisol    | Quartzipsamment | Brown to dark brown sand   | Natural substrate |
|  |            | Torripsamment   | White gypsum dune sand.  | Natural substrate |
|  |            | Ustifluent      | Brown to dark brown silt loam                                      | Natural substrate |
|  | Inceptisol | Cryumbrept      | Gray/dark brown extremely stoney coarse sandy                      | Natural substrate |
|  |            | Dystrochrept    | Dark yellowish brown micaceous loam                                | Natural substrate |

|  |          |              |  |                   |
|--|----------|--------------|--|-------------------|
|  |          | Haplumbrept  | Brown sandy loam                             | Natural substrate |
|  |          |              | Dark brown fine sandy loam                   | Natural substrate |
|  |          | Plaggept     | Very dark grayish brown silty loam           | Natural substrate |
|  |          | Ustocrept    | Pale brown dry silty clay loam               | Natural substrate |
|  |          | Xerumbrept   | Brown to dark brown gravelly fine sandy loam | Natural substrate |
|  | Mollisol | Agialboll    | Dark grayish brown silty loam                | Natural substrate |
|  |          | Agriudoll    | Vary dark grayish brown loam                 | Natural substrate |
|  |          | Argiustoll   | Very dark grayish brown silty loam           | Natural substrate |
|  |          | Cryoboroll   | Black loam                                   | Natural substrate |
|  |          |              | Very dark grayish brown loam                 | Natural substrate |
|  |          | Haplaquoll   | Gray silty clay                              | Natural substrate |
|  |          | Hapludoll    | Brown to dark brown sandy loam               | Natural substrate |
|  |          | Haplustall   | Grayish brown loam                           | Natural substrate |
|  |          | Paleustoll   | Very dark grayish brown loam                 | Natural substrate |
|  | Spodosol | Cryohumod    | Dark reddish brown, organic-rich, silty loam | Natural substrate |
|  | Udisol   | Hapludult    | Brown to dark brown loamy sand               | Natural substrate |
|  | Vertisol | Chromoxerert | Brown to dark brown clay                     | Natural substrate |

|       |           |                 |                      |                 |
|-------|-----------|-----------------|----------------------|-----------------|
| Water | Frost     | none            | Frost                | <i>EXCLUDED</i> |
|       | Ice       | none            | Ice                  | <i>EXCLUDED</i> |
|       | Snow      | Coarse Granular | Coarse Granular Snow | <i>EXCLUDED</i> |
|       |           | Fine Granular   | Fine Snow            | <i>EXCLUDED</i> |
|       |           | Medium Granular | Medium Granular Snow | <i>EXCLUDED</i> |
|       | Tap Water | none            | Tap water            | Water           |