Asset Wealth Prognosis

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SEE DOCUMENTATION OF SCRIPTS AND NOTEBOOKS:

CHAPTER

ONE

HARDWARE AND SOFTWARE REQUIREMENTS

1.1 This code was tested on a system with the following specifications:

- operating system: 20.04.1-Ubuntu SMP
- CPU: AMD EPYC 7443P 24-Core
- GPU: 1x NVIDIA RTX A6000

1.2 Software Requirements:

- Python Version: 3.8.8
- Tensorflow Version: 2.8
- Keras: 2.8

Further Python Package requirements are listed in the requirements.txt.

CHAPTER

TWO

DATA ACQUISITION & PREPROCESSING

1. Calculate Asset Wealth: `/src/dhs_preparation.py`.
2. Set Parameters for Satellite Data Retrieval inside `/src/config.py`.
3. Export satellite images from Google Earth Engine:
   1. `/src/ee_sentinel.py` for Sentinel-2 Data
   2. `/src/ee_viirs.py` for VIIRS Data
4. Move Files to corresponding Preprocessing Folders by using `/notebooks/split_geotiffs_for_preprocessing.ipynb`.
5. Preprocess GeoTIFFs: `/src/preprocess_geodata.py`.

CHAPTER

THREE

MODEL TRAINING

1. Set Parameters for Model Training inside `/src/config.py`.
2. Run `/src/train_directly.py` and login to Weights & Bias to track Model Training and Evaluation.

CHAPTER

FOUR

NOTEBOOKS

1. Use `/notebooks/asset_wealth_analysis.ipynb` to analyze the calculated Asset Wealth.
2. Use `/notebooks/asset_wealth_prognosis.ipynb` to analyze test results and predict Asset Wealth for Mozambique (2016, 2017,2019, 2020 and 2021).

4.1 src package

4.1.1 Submodules

4.1.2 src.config module

Configuration of variables for aquisition of satellite images and model training.

4.1.3 src.data_utils module

`src.data_utils.`**`calc_mean`**(*img_dir: str*, *img_list: list*, *input_height: int*, *input_width: int*, *clipping_values: list*, *channels: list*)

Calculate mean pixel values per channel over all input images

Parameters

- **`img_dir`** (*`str`*) – Path to image data
- **`input_height`** (*`int`*) – Pixel height of input
- **`input_width`** (*`int`*) – Pixel width of input
- **`clipping_values`** (*`list`*) – Interval of min and max values for clipping
- **`channels`** (*`list`*) – Channels to use; [] if all channels are to be used

Returns (np.array): Means of pixel values per channel

`src.data_utils.`**`calc_std`**(*means*, *img_dir: str*, *img_list: list*, *input_height: str*, *input_width: str*, *clipping_values: list*, *channels: list*)

Calculate standard deviation values per channel over all input images

Parameters

- **`means`** (*`np.array`*) – Result of calc_mean: Mean of pixel values for each channel
- **`img_dir`** (*`str`*) – Path to image data
- **`input_height`** (*`int`*) – Pixel height of input

- **input_width** (*int*) – Pixel width of input
- **clipping_values** (*list*) – Interval of min and max values for clipping
- **channels** (*list*) – Channels to use; [] if all channels are to be used

Returns (np.array): Standard deviation of pixel values per channel

src.data_utils.**combine_wealth_dfs**(*wealth_csv_path: str*)

Combines all label csv files to one.

Parameters **wealth_csv_path** (*str*) – Path to label csv files

Returns Pandas DataFrame containing all clusters

Return type complete_wealth_df (pd.DataFrame)

src.data_utils.**create_splits**(*img_dir: str*, *pre2015_path: str*, *wealth_path: str*, *urban_rural: str*, *subset=False*)

Create train/val and testsplit for cross validation.

Parameters

- **img_dir** (*str*) – Path to image data
- **pre2015_path** (*str*) – Path to test images with corresponding label dated older than 2015
- **wealth_path** (*str*) – Path to label csv files
- **urban_rural** (*str*) – One of [â€˜uâ€™,â€™râ€™,â€™urâ€™] to choose whether to use only urban/rural clusters or all data
- **subset** (*bool*) – Whether or not to use a subset (for testing)

Returns

List containing filenames for train and validation split X_test (list): List containing filenames for test split y_train_val (np.ndarray): Numpy array containing Asset Wealth (label data) for train and validation split y_test (np.ndarray): Numpy array containing Asset Wealth (label data) for test split

If pre2015_path is set also returns: X_test_pre2015 (list): List containing filenames for test split with corresponding label dated older than 2015 y_test_pre2015 (np.ndarray):Numpy array containing Asset Wealth (label data) for test split (dated older than 2015)

Return type X_train_val (list)

src.data_utils.**generator**(*img_dir: str*, *X: list*, *y: numpy.ndarray*, *batch_size: int*, *input_height: int*, *input_width: int*, *channel_size: int*)

Data generator to generate label and feature batches.

Parameters

- **img_dir** (*str*) – Path to image data
- **X** (*list*) – List containing filenames of split
- **y** (*np.ndarray*) – Array containing lbel values of split
- **batch_size** (*int*) – Size of training batches
- **input_height** (*int*) – Pixel height of input
- **input_width** (*int*) – Pixel width of input
- **channels** (*int*) – Number of channels

Returns batch_x (np.ndarray): Feature batch batch_y (np.ndarray): Label batch

`src.data_utils.`**`get_img_coordinates`**`(`*img: str*`)`

Extract the cluster coordinates from a given filename.

Parameters **`img`** (*`str`*) – Filename of image

Returns Latitude, longitude

Return type str, str

`src.data_utils.`**`get_kurtosis`**`(`*wealth_df: pandas.core.frame.DataFrame*`)`

Calculate the Kurtosis for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas DataFrame containing at least a column â€~WEALTH_INDEXâ€™

Returns Mean Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`get_label_for_img`**`(`*wealth_df: pandas.core.frame.DataFrame*, *img_filename: str*`)`

Get label data for a cluster based on the filename.

Parameters

- **`wealth_df`** (*`pd.DataFrame`*) – Pandas DataFrame containing all clusters
- **`img_dir`** – Path to image data

Returns Pandas DataFrame including the Asset Wealth Value of the image

Return type wealth_sentinel_df

`src.data_utils.`**`get_mean`**`(`*wealth_df: pandas.core.frame.DataFrame*`)`

Calculate the mean value for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas DataFrame containing at least a column â€~WEALTH_INDEXâ€™

Returns Mean Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`get_median`**`(`*wealth_df: pandas.core.frame.DataFrame*`)`

Calculate the Median Value for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas Dataframe containing at least a column â€~WEALTH_INDEXâ€™

Returns Median Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`get_skew`**`(`*wealth_df: pandas.core.frame.DataFrame*`)`

Calculate the Skewness for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas DataFrame containing at least a column â€~WEALTH_INDEXâ€™

Returns Mean Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`get_statistics`**(*csv_path: str*, *timespan_a: list*, *countries: list*, *timespan_b=False*, *timespan_c=False*)

Creates a dictionary that includes statistic values per country year and combined per timespan.

The dictionary has the following structure: statistics = { country_year: [], mean: [], median: [], std: [], var: [], skewness: [], kurtosis: [] } :param csv_path: Path to label csv files :type csv_path: str :param timespan_a: Timespan in years e.g. [2012,2013,2014] to include :type timespan_a: list :param countries: Countries to include :type countries: list :param timespan_b: Optional: Second timespan in years e.g. [2015] to include :type timespan_b: bool/list :param timespan_c: Optional: Third timespan in years e.g. [2016, 2017,2018,2019,2020] to include :type timespan_c: bool/list

Returns Dictionary including statistic values per country year and combined over timespan(s)

Return type statistics (dict)

`src.data_utils.`**`get_std`**(*wealth_df: pandas.core.frame.DataFrame*)

Calculate the Standard Deviation for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas DataFrame containing at least a column â€˜WEALTH_INDEXâ€™

Returns Mean Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`get_ur_statistics`**(*csv_path: str*, *timespan_a: list*, *countries: list*, *timespan_b=False*, *timespan_c=False*)

Creates a dictionary that includes statistic per region type (urban/rural) per timespan. The dictionary has the following keys: statistics = { year: [], ur: [], mean: [], median: [], std: [], var: [], skewness: [], kurtosis: [] }

Parameters

- **`csv_path`** (*`str`*) – Path to label csv files
- **`timespan_a`** (*`list`*) – Timespan in years e.g. [2012,2013,2014] to include
- **`countries`** (*`list`*) – Countries to include
- **`timespan_b`** (*`bool/list`*) – Optional: Second timespan in Years e.g. [2015] to include
- **`timespan_c`** (*`bool/list`*) – Optional: Third timespan in Years e.g. [2016, 2017,2018,2019,2020] to include

Returns Dictionary including statistic values per region type (urban/rural) per timespan.

Return type statistics (dict)

`src.data_utils.`**`get_var`**(*wealth_df: pandas.core.frame.DataFrame*)

Calculate the Variance for WEALTH_INDEX column of a Pandas DataFrame.

Parameters **`wealth_df`** – Pandas DataFrame containing at least a column â€˜WEALTH_INDEXâ€™

Returns Mean Asset Wealth of DataFrame

Return type float

`src.data_utils.`**`truncate`**(*f*, *n*)

Truncates a float f to n decimal places without rounding.

Parameters

- **`f`** – Float value
- **`n`** – Number of decimal places

4.1.4 src.dhs_preparation module

class src.dhs_preparation.**DHS_preparation**(*floor_recode: dict*, *toilet_recode: dict*, *water_recode: dict*, *country_code_dict: dict*, *features: list*, *info: list*, *dhs_survey_path: str*, *wealth_path: str*, *shape_path: str*, *geo_wealth_path: str*, *sustainlab_group_file: str*)

Bases: object

create_wealth_geo_df(*shape_file: str*)

Combine survey data including Asset Wealth with geocoordinates.

Parameters **shape_file** – Filename of DHS shapefile

recode_and_format_dhs(*filename: str*)

Recode DHS survey data and calculate Asset Wealth.

Parameters **filename** – Filename of DHS survey csv

split_sustainlab_clusters()

Split sustainlab cluster csv into separate csv files. Creates one csv file per survey (country/year).

src.dhs_preparation.**main**()

Recode dhs survey data and create label csv file for each survey including Asset Wealth and geocoordinates.

4.1.5 src.ee_sentinel module

src.ee_sentinel.**bounding_box**(*loc: ee.geometry.Geometry.Point*, *urban_rural: int*, *urban_radius: int*, *rural_radius: int*)

Function to get a square around point of interest. Rural : 10 km Radius Urban : 2 km Radius

Parameters

- **loc** (*ee.Geometry.Point*) – Geolocation of cluster (from DHS survey)
- **urban_rural** (*int*) – Binary encoding for type of region: 0 = urban, 1 = rural
- **urban_radius** (*int*) – Radius around coordinates for Urban regions in meter
- **rural_radius** (*int*) – Radius around coordinates for Rural regions in meter

Returns

bounding box around cluster coordinates with a size of 10x10km for rural/ 2x2km for Urban

Return type intermediate_box (ee.Geometry)

src.ee_sentinel.**download_local**(*survey_dir: str*)

Download images from GoogleDrive folder.

Parameters **survey_dir** (*str*) – Output directory for download

src.ee_sentinel.**get_image**(*cluster: object*, *urban_radius: int*, *rural_radius: int*, *country_code: str*, *MAX_CLOUD_PROBABILITY: int*)

Extract Information about cluster to get Sentinel-2 image for corresponding year and coordinates.

Parameters

- **cluster** (*DictReader object*) – Information about the Cluster (cluster number, coordinates, survey name, etc.)
- **survey_name** (*str*) – Name of the survey (COUNTRY_YEAR)

- **urban_radius** (*int*) – Radius around coordinates for Urban regions in meter
- **rural_radius** (*int*) – Radius around coordinates for Rural regions in meter
- **country_code** (*str*) – ISO code for survey country (COUNTRY)
- **MAX_CLOUD_PROBABILITY** (*int*) – %

Returns Latitude_Longitude_begin-end_COUNTRY_r/u_sidelength coordinates: 4 Nachkommastellen date format: YYYYMMDD country: Official 3 letters acronym (ISO) Rural/Urban: u or r side length: Sidelength (size) of tile in km with one decimal place.

Return type Requests Image from Earth Engine. Files are named by the following pattern

src.ee_sentinel.**get_survey_images**(*file_dir: str*, *survey_name: str*, *urban_radius: int*, *rural_radius: int*, *MAX_CLOUD_PROBABILITY: int*)

Get Sentinel-2 image for each Cluster and download from GoogleDrive.

Parameters

- **file_dir** (*str*) – Path to DHS survey csv file
- **survey_name** (*str*) – Name of the survey (COUNTRY_YEAR)
- **urban_radius** (*int*) – Radius around coordinates for Urban regions in meter
- **rural_radius** (*int*) – Radius around coordinates for Rural regions in meter
- **MAX_CLOUD_PROBABILITY** (*int*) – %

src.ee_sentinel.**maskClouds**(*img: ee.image.Image*, *MAX_CLOUD_PROBABILITY: int*)

Masking of clouds.

Parameters

- **img** (*ee.Image*) – Sentinel-2 image retrieved from ee
- **MAX_CLOUD_PROBABILITY** (*int*) – %

Returns CloudMasked GoogleEarthEngine image

Return type ee.Image

src.ee_sentinel.**sentinel_img_survey**(*img_dir: str*, *csv_dir: str*, *sentinel_done: str*, *urban_radius: int*, *rural_radius: int*, *MAX_CLOUD_PROBABILITY: int*)

Iterate over survey csvs and get Sentine-2 images for each cluster.

Parameters

- **img_dir** (*str*) – Path to directory where Sentinel-2 images are stored
- **csv_dir** (*str*) – Path to directory where DHS csv files are stored
- **sentinel_done** (*str*) – Filepath for file to document for which surveys were are already completed
- **urban_radius** (*int*) – Radius around coordinates for Urban rgions in meter
- **rural_radius** (*int*) – Radius around coordinates for Rural regions in meter
- **MAX_CLOUD_PROBABILITY** (*int*) – %

4.1.6 src.ee_viirs module

`src.ee_viirs.`**`bounding_box`**`(`*loc*, *urban_rural*, *urban_radius*, *rural_radius*`)`

Function to get a square around point of interest. Rural : 10 km Radius Urban : 2 km Radius

Parameters

- **`loc`** (*`ee.Geometry.Point`*) – Geolocation of cluster (from DHS survey)
- **`urban_rural`** (*`int`*) – Binary encoding for type of region: 0 = urban, 1 = rural
- **`urban_radius`** (*`int`*) – Radius around coordinates for Urban regions in meter
- **`rural_radius`** (*`int`*) – Radius around coordinates for Rural regions in meter

Returns

bounding box around cluster coordinates with a size of 10x10km for rural/ 2x2km for Urban

Return type intermediate_box (ee.Geometry)

`src.ee_viirs.`**`download_local`**`(`*survey_dir*`)`

Download images from GoogleDrive folder.

Parameters **`survey_dir`** (*`str`*) – Output directory for download

`src.ee_viirs.`**`get_image`**`(`*cluster*, *survey_name*, *urban_radius*, *rural_radius*`)`

Extract Information about cluster to get Sentinel-2 image for corresponding year and coordinates.

Parameters

- **`cluster`** (*`DictReader object`*) – Information about the Cluster (cluster number, coordinates, survey name, etc.)
- **`survey_name`** (*`str`*) – Name of the survey (COUNTRY_YEAR)
- **`urban_radius`** (*`int`*) – Radius around coordinates for Urban regions in meter
- **`rural_radius`** (*`int`*) – Radius around coordinates for Rural regions in meter
- **`country_code`** (*`str`*) – ISO code for survey country (COUNTRY)
- **`MAX_CLOUD_PROBABILITY`** (*`int`*) – %

Returns Latitude_Longitude_begin-end_COUNTRY_r/u_sidelength coordinates: 4 Nachkommastellen date format: YYYYMMDD country: Official 3 letters acronym (ISO) Rural/Urban: u or r side length: Sidelength (size) of tile in km with one decimal place.

Return type Requests Image from Earth Engine. Files are named by the following pattern

`src.ee_viirs.`**`get_survey_images`**`(`*file_dir*, *survey_name*, *urban_radius*, *rural_radius*`)`

Get VIIRS Image for each Cluster and download from GoogleDrive.

Parameters

- **`file_dir`** (*`str`*) – Path to DHS survey csv file
- **`survey_name`** (*`str`*) – Name of the survey (COUNTRY_YEAR)
- **`urban_radius`** (*`int`*) – Radius around coordinates for Urban regions in meter
- **`rural_radius`** (*`int`*) – Radius around coordinates for Rural regions in meter

`src.ee_viirs.`**`viirs_img_survey`**(*img_dir*, *csv_dir*, *viirs_done*, *urban_radius*, *rural_radius*)

Iterate over survey csvs and get VIIRS images for each cluster.

Parameters

- **img_dir** (*str*) – Path to directory where VIIRS images are stored
- **csv_dir** (*str*) – Path to directory where DHS csv files are stored
- **sentinel_done** (*str*) – Filepath for file to document for which surveys were are already completed
- **urban_radius** (*int*) – Radius around coordinates for Urban rgions in meter
- **rural_radius** (*int*) – Radius around coordinates for Rural regions in meter

4.1.7 src.preprocess_geodata module

`src.preprocess_geodata.`**`main`**(*img_path: str*, *ur: str*, *year: str*, *input_height: str*, *input_width: str*, *clipping_values: list*, *channels: list*, *add_img_path=False*, *standardize=False*)

Preprocessing of GeoTIFFs. Preprocessing includes slicing to desired input size and standardizing the image data.

Parameters

- **img_path** (*str*) – Path to image data
- **ur** (*str*) – â€˜uâ€™ for urban, â€˜râ€™ for rural
- **year** (*str*) – timespan (2012_2014 / 2016_2020) or all data
- **input_height** (*int*) – Desired input height
- **input_width** (*int*) – Desired input width
- **clipping_values** (*list*) – Interval of min and max values for clipping
- **channels** (*list*) – List of channels to use. [] to use all channels.
- **add_img_path** (*bool/str*) – Optional: Path to image data to add (eg. for combining Sentinel2 and VIIRS)
- **standardize** – Optional: Whether or not to standardize image data (e.g. standardization is not needed when already normalized Sentinel-2 and VIIRS data is merged)

`src.preprocess_geodata.`**`slice_to_input_size`**(*array: numpy.ndarray*, *input_height: int*, *input_width: int*)

Slice image array to desired input shape.

Parameters

- **array** (*np.ndarray*) – Numpy array containing image data
- **input_height** (*int*) – Uniform image height to slice to
- **input_width** (*int*) – Uniform image width to slice to

Returns Numpy array containing image data in shape of input height/width and Bandwidth

Return type array (np.array)

`src.preprocess_geodata.`**`standardize_resize`**(*img: str*, *img_path: str*, *input_height: str*, *input_width: str*, *clipping_values: list*, *means=False*, *stds=False*, *add_img_path=False*, *standardize=False*)

Standardize and resize GeoTIFFs. Standardization is performed per band using Standard Scaler. Resizing is performed by slicing to the center of the image in shape of provided input Size. For VIIRS images, the band is tripled to fit RGB input shape of common CNNs. Standardized and resized images are stored in a new GeoTIFF.

Parameters

- **img** (*str*) – Filename of image to normalize and resize
- **img_path** (*str*) – Path to image data
- **input_height** (*int*) – Desired input height
- **input_width** (*int*) – Desired input width
- **clipping_values** (*list*) – Interval of min and max values for clipping
- **means** (*bool/np.ndarray*) – Optional: Result of calc_mean: Mean of pixel values for each channel
- **stds** (*bool/np.ndarray*) – Optional: Result of calc_mean: Standard deviation of pixel values for each channel
- **add_img_path** (*bool/str*) – Optional: Path to image data to add (eg. for combining Sentinel-2 and VIIRS)
- **standardize** (*bool*) – Optional: Whether or not to standardize image data (e.g. standardization is not needed when already normalized Sentinel-2 and VIIRS data is merged)

4.1.8 src.rename_viirs module

src.rename_viirs.**get_center_coords**(*img_path=<class 'str'>*)

Get center coordinates of a GeoTIFF.

Parameters **img_path** (*str*) – Path to GeoTIFF

Returns Center Longitude Value of Image lat (float): Center Latitude Value of Image

Return type long (float)

src.rename_viirs.**main**(*img_dir: str*)

Rename all VIIRS GeoTIFFs from DIS22 according to filename pattern: Latitude_Longitude_begin-end_COUNTRY_r/u_sidelength coordinates: 4 Nachkommastellen date format: YYYYMMDD country: Official 3 letters acronym (ISO) Rural/Urban: u or r side length: Sidelength (size) of tile in km with one decimal place.

Parameters **img_dir** – Path to image data

4.1.9 src.resnet50 module

class src.resnet50.**ResNet50v2_hyperspectral**(*img_w: int*, *img_h: int*, *channels: int*)

Bases: object

load_resnet50v2()

Returns a Resnet-50v2 *keras.Model* instance fitted to hyperspectral/RGB image input.

4.1.10 src.train module

`src.train.main`(*img_dir: str*, *csv_path: str*, *pre2015_path: str*, *model_name: str*, *k: int*, *input_height: int*, *input_width: int*, *img_source: str*, *urban_rural: str*, *channel_size: int*, *batch_size: int*, *epochs: int*, *subset: bool*)

Train a Model with the Parameters set in config.py.

Parameters

- **img_dir** (*str*) – Path to image data
- **csv_path** (*str*) – Path to label csv files
- **pre2015_path** (*str*) – Path to image data older than 2015; if all data is used for training this should be False.
- **model_name** (*str*) – One of [â€~vgg19â€™, â€~resnet50â€™] to choose which model is used
- **k** (*int*) – Number of folds for cross validation
- **input_height** (*int*) – Pixel height of input
- **input_width** (*int*) – Pixel width of input
- **img_source** (*str*) – One of [â€~s2â€™, â€~viirsâ€™] to choose whether Sentinel-2, VIIRS (nightlight) or combined data is used
- **urban_rural** (*str*) – On of [â€~uâ€™,â€™râ€™,â€™urâ€™] to choose whether only urban or only rural clusters are used
- **channels** (*list*) – Channels to use; [] to use all channels
- **channel_size** (*int*) – Number of channels (3 for RGB (VIIRS), 13 for all Sentinel-2 channels, 14 for all channels) !Nightlight channel is transformed to 3 channels for model compatibility
- **batch_size** (*int*) – Size of training batches
- **epochs** (*int*) – Number of training epochs
- **subset** (*bool*) – Whether or not to use a subset to test the process

4.1.11 src.vgg19 module

class `src.vgg19.VGG19_hyperspectral`(*img_w: int*, *img_h: int*, *channels: int*)

Bases: `object`

`load_vgg19()`

Returns a VGG19 *keras.Model* instance fitted to hyperspectral/RGB image input.

4.1.12 Module contents

4.2 Notebooks

4.2.1 Statistical Analysis of Asset Wealth

[1]:
```
import os
import glob
import sys

sys.path.append("..")

import pandas as pd

import matplotlib.pyplot as plt
import matplotlib.patches as mpatches

from src.data_utils import get_mean
from src.data_utils import get_median
from src.data_utils import get_std
from src.data_utils import get_var
from src.data_utils import get_skew
from src.data_utils import get_kurtosis
from src.data_utils import get_ur_statistics
from src.data_utils import get_statistics
```

Compare urban and rural Regions over Time

[2]:
```
csv_path='/mnt/datadisk/data/surveys/asset/dhs_data/label_data/'
countries = ['Malawi', 'Kenya', 'Democratic Republic of Congo',  'Rwanda', 'Zambia',
↪'Uganda', 'Tanzania', 'Ethiopia', 'Mozambique', 'Zimbabwe']
```

[3]:
```
statistics_ur = get_ur_statistics(csv_path=csv_path, timespan_a=range(2012,2015),␣
↪countries=countries, timespan_b = range(2016,2021), timespan_c=range(2015,2016))
```

[4]:
```
statistics_ur_df = pd.DataFrame.from_dict(statistics_ur, orient='columns')
print(statistics_ur_df.shape)
statistics_ur_df.head(2)
```

```
(6, 8)
```

[4]:
```
        year     ur      mean    median       std       var  skewness  \
0  2012-2014  urban  0.732320  0.676740  0.831303  0.691065  0.453175
1  2012-2014  rural -0.426892 -0.435667  0.496990  0.246999 -0.350300

   kurtosis
0  0.085632
1  2.431044
```

[6]:
```
mosaic = """
    AB
    CD
    EF
    """
fig = plt.figure(constrained_layout=True)
axes = fig.subplot_mosaic(mosaic,sharey=True)

plt.rcParams["figure.figsize"]=(20,10)
for ax in [axes['A'],axes['B'],axes['C'],axes['D'],axes['E'],axes['F']]:
    ax.tick_params(axis='both', which='major', labelsize=16)
    ax.set_axisbelow(True)



fig.suptitle("Statistische Analyse des Asset Wealth nach Art der Region", x=.4, y=1.1,␣
↪fontsize=32)

axes['A'].set_title('Arithmetisches Mittel des Asset Wealth', fontsize=20, loc='left')
means = pd.pivot_table(statistics_ur_df,values="mean",index="year",columns="ur")
means.plot(
    kind='barh', ax=axes['A'], color=['#67a9cf', '#ef8a62'])
axes['A'].get_legend().remove()
axes['A'].set_yticks(statistics_ur_df.index[:3], means.index.unique())
axes['A'].set_xlabel('Arithmetisches Mittel', fontsize=16)
axes['A'].set_ylabel('Zeitraum', fontsize=16)
axes['A'].grid(axis='x',color='lightgrey')
axes['A'].spines['top'].set_visible(False)
axes['A'].spines['right'].set_visible(False)


axes['B'].set_title('Kurtosis des Asset Wealth', fontsize=20, loc='left')
pd.pivot_table(statistics_ur_df,values="kurtosis",index="year",columns="ur").plot(
    kind='barh', width=.5, ax=axes['B'], color=['#67a9cf', '#ef8a62'])
axes['B'].get_legend().remove()
axes['B'].set_ylabel('Zeitraum', fontsize=16)
axes['B'].grid(axis='x',color='lightgrey')
axes['B'].spines['top'].set_visible(False)
axes['B'].spines['right'].set_visible(False)

axes['C'].set_title('Median des Asset Wealth', fontsize=20, loc='left')
pd.pivot_table(statistics_ur_df,values="median",index="year",columns="ur").plot(
    kind='barh', width=.5,ax=axes['C'], color=['#67a9cf', '#ef8a62'])
axes['C'].get_legend().remove()
axes['C'].set_xlabel('Median', fontsize=16)
axes['C'].set_ylabel('Zeitraum', fontsize=16)
axes['C'].grid(axis='x',color='lightgrey')
axes['C'].spines['top'].set_visible(False)
axes['C'].spines['right'].set_visible(False)

axes['D'].set_title('Schiefe des Asset Wealth', fontsize=20, loc='left')
pd.pivot_table(statistics_ur_df,values="skewness",index="year",columns="ur").plot(
    kind='barh', width=.5, ax=axes['D'], color=['#67a9cf', '#ef8a62'])
```
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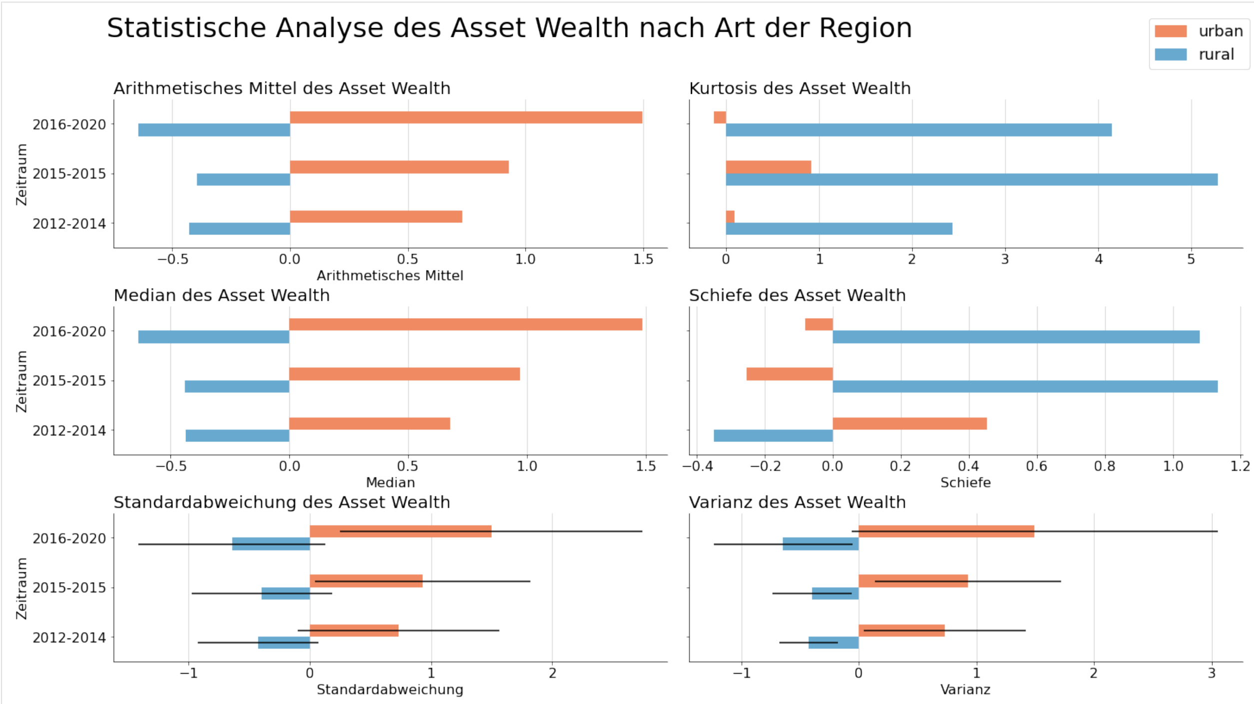
```
axes['D'].get_legend().remove()
axes['D'].set_xlabel('Schiefe', fontsize=16)
axes['D'].set_ylabel('Zeitraum', fontsize=16)
axes['D'].grid(axis='x',color='lightgrey')
axes['D'].spines['top'].set_visible(False)
axes['D'].spines['right'].set_visible(False)


axes['E'].set_title('Standardabweichung des Asset Wealth', fontsize=20, loc='left')
pd.pivot_table(statistics_ur_df,values=["mean",'std'],index="year",columns="ur").plot(
    kind='barh', y='mean', width=.5, ax=axes['E'], xerr='std', color=['#67a9cf', '#ef8a62
↪'])
axes['E'].get_legend().remove()
axes['E'].set_xlabel('Standardabweichung', fontsize=16)
axes['E'].set_ylabel('Zeitraum', fontsize=16)
axes['E'].grid(axis='x',color='lightgrey')
axes['E'].spines['top'].set_visible(False)
axes['E'].spines['right'].set_visible(False)


axes['F'].set_title('Varianz des Asset Wealth', fontsize=20, loc='left')
pd.pivot_table(statistics_ur_df,values=["mean",'var'],index="year",columns="ur").plot(
    kind='barh', y='mean', width=.5, ax=axes['F'], xerr='var', color=['#67a9cf', '#ef8a62
↪'])
axes['F'].get_legend().remove()
axes['F'].set_xlabel('Varianz', fontsize=16)
axes['F'].set_ylabel('Zeitraum', fontsize=16)
axes['F'].grid(axis='x',color='lightgrey')
axes['F'].spines['top'].set_visible(False)
axes['F'].spines['right'].set_visible(False)


patch_urban = mpatches.Patch(color='#ef8a62', label='urban')
patch_rural = mpatches.Patch(color='#67a9cf', label='rural')
fig.legend(handles=[patch_urban, patch_rural], fontsize=18, loc='upper right')
# plt.savefig('./asset_wealth_statistic_analysis.png', dpi=300, bbox_inches='tight', pad_
↪inches = 0)
plt.show()
```




```
[7]: statistics_ur_df['year'] = statistics_ur_df.year.apply(lambda x:x.replace('_','-'))
     statistics_ur_df['year'] = statistics_ur_df.year.apply(lambda x: x.replace('2015-2015',
     ↪'2015'))
     statistics_ur_df.dropna().sort_values(by=['year'])
```

```
[7]:         year     ur      mean    median       std       var  skewness  \
     0  2012-2014  urban  0.732320  0.676740  0.831303  0.691065  0.453175
     1  2012-2014  rural -0.426892 -0.435667  0.496990  0.246999 -0.350300
     4       2015  urban  0.929695  0.971463  0.888563  0.789544 -0.252657
     5       2015  rural -0.394422 -0.440112  0.580919  0.337467  1.132054
     2  2016-2020  urban  1.497189  1.486528  1.246898  1.554755 -0.082131
     3  2016-2020  rural -0.642661 -0.633979  0.768087  0.589958  1.080916

        kurtosis
     0  0.085632
     1  2.431044
     4  0.912855
     5  5.286251
     2 -0.134592
     3  4.150475
```

Compare Statistics per Survey

[8]:
```
statistics = get_statistics(csv_path=csv_path, timespan_a=range(2012,2015),␣
↪countries=countries, timespan_b = range(2016,2021), timespan_c=range(2015,2016))
```

[9]:
```
cc_mapping = {
    'CD': 'COD',
    'ET': 'ETH',
    'KE': 'KEN',
    'MW': 'MWI',
    'MZ': 'MOZ',
    'RW': 'RWA',
    'TZ': 'TZA',
    'UG': 'UGA',
    'ZM': 'ZMB',
    'ZW': 'ZWE'
}
```

[10]:
```
statistics_df = pd.DataFrame.from_dict(statistics, orient='columns')
statistics_df = statistics_df.sort_values(by=['country_year']).reset_index(drop=True)
statistics_df['country_year'] = statistics_df.country_year.apply(lambda x: x.replace(x[:
↪2], cc_mapping[x[:2]]).replace('_', ' ') if not x.startswith('kombiniert') else x.
↪replace('kombiniert_', 'Kombiniert ').replace('_','-'))
statistics_df.loc[statistics_df.country_year=='Kombiniert 2016-2020', 'country_year'] =
↪'2016-2020'
statistics_df.loc[statistics_df.country_year=='Kombiniert 2012-2014', 'country_year'] =
↪'2012-2014'
statistics_df.loc[statistics_df.country_year=='Kombiniert 2015-2015', 'country_year'] =
↪'2015'
statistics_df.dropna()
```

[10]:

	country_year	mean	median	std	var	skewness	kurtosis
0	COD 2014	0.038550	-0.390554	0.958625	0.918962	2.005833	3.031307
1	ETH 2016	0.012098	-0.381761	0.929815	0.864555	0.923636	-0.466208
2	KEN 2014	-0.002535	-0.040012	0.846506	0.716573	0.031881	0.459236
3	KEN 2015	-0.001298	-0.087786	0.775691	0.601697	-0.001202	0.677301
4	MWI 2014	0.003037	-0.421321	0.818947	0.670674	1.185901	0.248446
5	MWI 2015	-0.066928	-0.355052	0.678299	0.460089	1.820677	2.835156
6	MWI 2016	0.213140	-0.204208	0.868516	0.754319	1.053283	0.232369
7	MOZ 2015	0.013473	-0.375884	1.469633	2.159821	0.596114	-0.635971
8	MOZ 2018	-0.016615	-0.815378	1.832815	3.359211	0.549163	-1.223835
9	RWA 2014	-0.151484	-0.320774	0.550205	0.302726	2.661513	7.245296
10	RWA 2015	0.095847	-0.292310	0.877292	0.769642	1.595143	1.368602
11	RWA 2020	0.002184	-0.436307	1.324332	1.753856	1.179800	0.752779
12	TZA 2015	0.145819	-0.158977	0.889375	0.790989	0.608331	-0.860105
13	TZA 2016	-0.448258	-0.642479	0.553245	0.306080	1.637034	1.984532
14	UGA 2014	0.096341	-0.138693	0.836245	0.699306	1.024133	0.407601
15	UGA 2015	-0.147538	-0.283633	0.857924	0.736034	1.497002	1.686292
16	UGA 2019	0.019539	-0.389447	1.398700	1.956362	1.135502	0.600526
17	ZMB 2014	-0.023153	-0.377790	0.845999	0.715714	1.141197	0.337275
18	ZMB 2018	-0.006915	-0.685355	1.797500	3.231007	0.795110	-0.548185
19	ZWE 2015	0.005259	-0.367102	0.860724	0.740845	0.196717	-1.641054
20	2012^a€“2014	-0.004615	-0.194061	0.848463	0.719890	0.856188	1.222880

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```
21          2015  0.022697 -0.283227  0.926333  0.858093  0.841734  0.610966
22    2016^a€“2020  0.001080 -0.415219  1.357643  1.843195  0.966412  0.410702
```

[11]:
```
c2012 = '#ef8a62'
c2015 = '#bababa'
c2016 = '#67a9cf'
colors = []
for cy in statistics_df.country_year.to_list():
    if any(str(year) in cy for year in range(2012,2015)):
        colors.append(c2012)
    elif '2015' in cy:
        colors.append(c2015)
    elif any(str(year) in cy for year in range(2016,2021)):
        colors.append(c2016)
```

[12]:
```
mosaic = """
    AB
    CD
    EF
    """
fig = plt.figure(constrained_layout=True)
axes = fig.subplot_mosaic(mosaic,sharex=True)

plt.rcParams["figure.figsize"]=(20,10)
for ax in [axes['A'],axes['B'],axes['C'],axes['D'],axes['E'],axes['F']]:
    ax.tick_params(axis='both', which='major', labelsize=18)
    ax.set_axisbelow(True)

fig.suptitle("Statistische Analyse des Asset Wealth nach Umfragejahr und -land", x=.42,␣
↪y=1.1, fontsize=32)

patch2012 = mpatches.Patch(color=c2012, label='2012-2014')
patch2015 = mpatches.Patch(color=c2015, label='2015')
patch2016 = mpatches.Patch(color=c2016, label='2016-2020')



axes['A'].set_title('Arithmetisches Mittel des Asset Wealth', fontsize=26, loc='left')
statistics_df['mean'].plot(kind='bar', ax=axes['A'], color=colors)#.set_
↪xticks(statistics_df.index[:-1], statistics_df.country_year.iloc[:-1])
axes['A'].set_ylabel('$\it{M}$', fontsize=22)
axes['A'].grid(axis='y',color='lightgrey')
axes['A'].spines['top'].set_visible(False)
axes['A'].spines['right'].set_visible(False)

axes['B'].set_title('Kurtosis des Asset Wealth', fontsize=26, loc='left')
statistics_df['kurtosis'].plot(kind='bar', width=.5, ax=axes['B'], color=colors)
axes['B'].set_ylabel('$\it{K}$', fontsize=22)
axes['B'].grid(axis='y',color='lightgrey')
axes['B'].spines['top'].set_visible(False)
axes['B'].spines['right'].set_visible(False)
```

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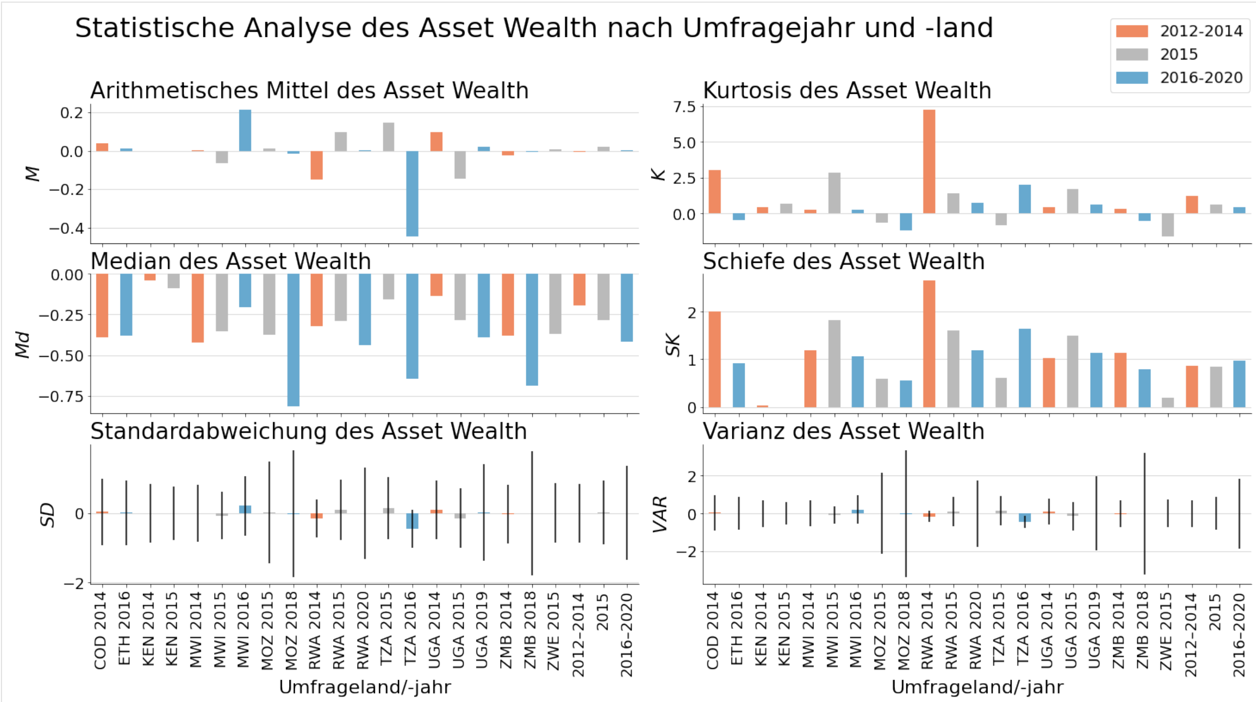
```
axes['C'].set_title('Median des Asset Wealth', fontsize=26, loc='left')
statistics_df['median'].plot(kind='bar', width=.5,ax=axes['C'], color=colors)#.set_
↪xticks(statistics_df.index[:-1], statistics_df.country_year.iloc[:-1])
axes['C'].set_xticks(statistics_df.index, statistics_df.country_year, fontsize=18)
axes['C'].set_ylabel('$\it{Md}$', fontsize=22)
axes['C'].set_xlabel('Umfrageland/-jahr', fontsize=22)
axes['C'].grid(axis='y',color='lightgrey')
axes['C'].spines['top'].set_visible(False)
axes['C'].spines['right'].set_visible(False)

axes['D'].set_title('Schiefe des Asset Wealth', fontsize=26, loc='left')
statistics_df['skewness'].plot(kind='bar', width=.5, ax=axes['D'], color=colors)
axes['D'].set_xticks(statistics_df.index, statistics_df.country_year, fontsize=18)
axes['D'].set_ylabel('$\it{SK}$', fontsize=22)
axes['D'].set_xlabel('Umfrageland/-jahr', fontsize=22)
axes['D'].grid(axis='y',color='lightgrey')
axes['D'].spines['top'].set_visible(False)
axes['D'].spines['right'].set_visible(False)

axes['E'].set_title('Standardabweichung des Asset Wealth', fontsize=26, loc='left')
statistics_df.plot(kind='bar', y='mean', width=.5, ax=axes['E'], yerr='std',␣
↪color=colors)
axes['E'].set_xticks(statistics_df.index, statistics_df.country_year, fontsize=18)
axes['E'].set_ylabel('$\it{SD}$', fontsize=22)
axes['E'].set_xlabel('Umfrageland/-jahr', fontsize=22)
axes['E'].grid(axis='y',color='lightgrey')
axes['E'].spines['top'].set_visible(False)
axes['E'].spines['right'].set_visible(False)
axes['E'].get_legend().remove()

axes['F'].set_title('Varianz des Asset Wealth', fontsize=26, loc='left')
statistics_df.plot(kind='bar', y='mean', width=.5, ax=axes['F'], yerr='var',␣
↪color=colors)
axes['F'].get_legend().remove()
axes['F'].set_xticks((statistics_df.index), statistics_df.country_year, fontsize=18)
axes['F'].set_ylabel('$\it{VAR}$', fontsize=22)
axes['F'].set_xlabel('Umfrageland/-jahr', fontsize=22)
axes['F'].grid(axis='y',color='lightgrey')
axes['F'].spines['top'].set_visible(False)
axes['F'].spines['right'].set_visible(False)

fig.legend(handles=[patch2012, patch2015, patch2016], fontsize=18, loc='upper right')
# plt.savefig('./asset_wealth_statistic_analysis.png', dpi=300, bbox_inches='tight', pad_
↪inches = 0)
plt.show()
```



[13]:
```python
statistics_df[['country_year', 'mean', 'median', 'std', 'var', 'skewness', 'kurtosis']]
```

[13]:

	country_year	mean	median	std	var	skewness	kurtosis
0	COD 2014	0.038550	-0.390554	0.958625	0.918962	2.005833	3.031307
1	ETH 2016	0.012098	-0.381761	0.929815	0.864555	0.923636	-0.466208
2	KEN 2014	-0.002535	-0.040012	0.846506	0.716573	0.031881	0.459236
3	KEN 2015	-0.001298	-0.087786	0.775691	0.601697	-0.001202	0.677301
4	MWI 2014	0.003037	-0.421321	0.818947	0.670674	1.185901	0.248446
5	MWI 2015	-0.066928	-0.355052	0.678299	0.460089	1.820677	2.835156
6	MWI 2016	0.213140	-0.204208	0.868516	0.754319	1.053283	0.232369
7	MOZ 2015	0.013473	-0.375884	1.469633	2.159821	0.596114	-0.635971
8	MOZ 2018	-0.016615	-0.815378	1.832815	3.359211	0.549163	-1.223835
9	RWA 2014	-0.151484	-0.320774	0.550205	0.302726	2.661513	7.245296
10	RWA 2015	0.095847	-0.292310	0.877292	0.769642	1.595143	1.368602
11	RWA 2020	0.002184	-0.436307	1.324332	1.753856	1.179800	0.752779
12	TZA 2015	0.145819	-0.158977	0.889375	0.790989	0.608331	-0.860105
13	TZA 2016	-0.448258	-0.642479	0.553245	0.306080	1.637034	1.984532
14	UGA 2014	0.096341	-0.138693	0.836245	0.699306	1.024133	0.407601
15	UGA 2015	-0.147538	-0.283633	0.857924	0.736034	1.497002	1.686292
16	UGA 2019	0.019539	-0.389447	1.398700	1.956362	1.135502	0.600526
17	ZMB 2014	-0.023153	-0.377790	0.845999	0.715714	1.141197	0.337275
18	ZMB 2018	-0.006915	-0.685355	1.797500	3.231007	0.795110	-0.548185
19	ZWE 2015	0.005259	-0.367102	0.860724	0.740845	0.196717	-1.641054
20	2012^a€“2014	-0.004615	-0.194061	0.848463	0.719890	0.856188	1.222880
21	2015	0.022697	-0.283227	0.926333	0.858093	0.841734	0.610966
22	2016^a€“2020	0.001080	-0.415219	1.357643	1.843195	0.966412	0.410702

4.2.2 Predict Asset Wealth for Testset and Mozambique

Predict Asset Wealth for Testset

[1]:
```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
os.environ["CUDA_DEVICE_ORDER"]="PCI_BUS_ID"
os.environ["CUDA_VISIBLE_DEVICES"]="2"
```

[2]:
```
import sys

sys.path.append("..")

from tensorflow import keras
from keras import optimizers, models

import matplotlib.pyplot as plt
from matplotlib import colors

import pandas as pd
import geopandas as gpd
from pyproj import CRS

import numpy as np
from tqdm.notebook import tqdm
import rasterio

from src.data_utils import combine_wealth_dfs
from src.data_utils import get_label_for_img
from src.data_utils import create_splits

crs = CRS("EPSG:4326")
```

Import Data

Satellite Images

[3]:
```
viirs_s2_path = '/mnt/datadisk/data/VIIRS_Sentinel2/asset/urban/all/'
viirs_path = '/mnt/datadisk/data/VIIRS/preprocessed/asset/rural//all/'
```

[4]:
```
all_urban_data = os.listdir(viirs_s2_path)
len(all_urban_data)
```

[4]:
```
2458
```

[5]:
```
all_rural_data = os.listdir(viirs_path)
len(all_rural_data)
```

[5]:
```
5602
```

Geographic Information

[6]:
```
countries = list(set([x.split('_')[3] for x in all_urban_data]))
countries
```

[6]:
```
['UGA', 'COD', 'MOZ', 'MWI', 'ETH', 'ZMB', 'KEN', 'TZA', 'RWA', 'ZWE']
```

[7]:
```
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
countries_gdf = world[world.iso_a3.isin(countries)]
countries_gdf
```

[7]:
```
       pop_est continent              name iso_a3  gdp_md_est  \
1     53950935    Africa          Tanzania    TZA    150600.0
11    83301151    Africa  Dem. Rep. Congo    COD     66010.0
13    47615739    Africa             Kenya    KEN    152700.0
48    13805084    Africa          Zimbabwe    ZWE     28330.0
70    15972000    Africa            Zambia    ZMB     65170.0
71    19196246    Africa            Malawi    MWI     21200.0
72    26573706    Africa        Mozambique    MOZ     35010.0
165  105350020    Africa          Ethiopia    ETH    174700.0
168   39570125    Africa            Uganda    UGA     84930.0
169   11901484    Africa            Rwanda    RWA     21970.0

                                              geometry
1    POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...
11   POLYGON ((29.34000 -4.49998, 29.51999 -5.41998...
13   POLYGON ((39.20222 -4.67677, 37.76690 -3.67712...
48   POLYGON ((31.19141 -22.25151, 30.65987 -22.151...
70   POLYGON ((30.74001 -8.34001, 31.15775 -8.59458...
71   POLYGON ((32.75938 -9.23060, 33.73972 -9.41715...
72   POLYGON ((34.55999 -11.52002, 35.31240 -11.439...
165  POLYGON ((47.78942 8.00300, 44.96360 5.00162, ...
168  POLYGON ((33.90371 -0.95000, 31.86617 -1.02736...
169  POLYGON ((30.41910 -1.13466, 30.81613 -1.69891...
```

Urban Data

[8]:
```
X_train_val, X_test, y_train_val, y_test = create_splits(img_dir='/mnt/datadisk/data/
↪VIIRS_Sentinel2/asset/urban/all/', wealth_path='/home/stoermer/Sentinel/gps_csv/',␣
↪urban_rural='u', pre2015_path=False)
```

```
Gathering Label Data
```

```
100%|^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^
↪^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^
↪a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^
↪^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^| 2458/2458 [01:03<00:00,␣
↪38.76it/s]
```

[9]:
```
wealth_df = combine_wealth_dfs('/home/stoermer/Sentinel/gps_csv/')

urban_test_labels = pd.DataFrame()
```

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```
for x in tqdm(X_test):
    urban_test_labels = pd.concat([urban_test_labels, get_label_for_img(wealth_df, x)])
urban_test_labels
```

```
  0%|          | 0/492 [00:00<?, ?it/s]
```

[9]:

```
    WEALTH_INDEX  SURVEY_YEAR    LATNUM  LONGNUM
0       1.071443         2015  -17.9025  30.6523
0      -0.068987         2014   -9.8081  29.0395
0       2.655006         2013   -4.3835  15.3125
0       1.668783         2019    2.7515  32.2981
0       1.278176         2015  -20.1791  28.6178
..           ...          ...       ...      ...
0       0.780936         2016   13.3427  39.7597
0       0.980313         2016   -5.7441  34.8325
0       0.135483         2019   -2.7007  29.0006
0       2.779817         2018  -25.8828  32.5081
0       0.327767         2016    7.2420  37.8950

[492 rows x 4 columns]
```

Get Predictions of Best Model

[10]:

```
model = keras.models.load_model('./vgg19_viirs_s2_u.h5')
```

[11]:

```
data_urban = np.zeros(shape=(len(X_test), 14, 200, 200))
for index, img in tqdm(enumerate(X_test)):
    # Read in each Image
    with rasterio.open(os.path.join(viirs_s2_path, img)) as i:
        array = i.read().astype("float32")

    # Ensure that the Array is not empty
    array[np.isnan(array)] = 0
    assert not np.any(np.isnan(array)), "Float"

    # Add to batch
    data_urban[index] = array

    # Check if batch is already full (Note: Index in batch array is from 0...4 hence we␣
↪need to add +1 to batch_ele)
data_urban = data_urban.transpose(0, 2, 3, 1)
preds_urban = model.predict(data_urban)
len(preds_urban)
```

```
0it [00:00, ?it/s]
```

[11]:

```
492
```

Create Geo DataFrames for Groundtruth and Predictions

[12]:
```
geometry = gpd.points_from_xy(urban_test_labels.LONGNUM, urban_test_labels.LATNUM)

true_urban_wealth_df = gpd.GeoDataFrame(urban_test_labels,
                        geometry=geometry,
                        crs=crs
                       )
true_urban_wealth_df['COUNTRY_CODE'] = [x.split('_')[3] for x in X_test]
true_urban_wealth_df = true_urban_wealth_df[['SURVEY_YEAR', 'geometry','COUNTRY_CODE',
↪'WEALTH_INDEX']]
true_urban_wealth_df.head(3)
```

[12]:
```
   SURVEY_YEAR                    geometry COUNTRY_CODE  WEALTH_INDEX
0         2015  POINT (30.65230 -17.90250)          ZWE      1.071443
0         2014   POINT (29.03950 -9.80810)          ZMB     -0.068987
0         2013   POINT (15.31250 -4.38350)          COD      2.655006
```

[13]:
```
predicted_urban_wealth_df = true_urban_wealth_df.loc[:,['SURVEY_YEAR', 'geometry']]
predicted_urban_wealth_df['WEALTH_INDEX'] = preds_urban
predicted_urban_wealth_df
```

[13]:
```
    SURVEY_YEAR                    geometry  WEALTH_INDEX
0          2015  POINT (30.65230 -17.90250)      1.538016
0          2014   POINT (29.03950 -9.80810)      0.407157
0          2013   POINT (15.31250 -4.38350)      2.204992
0          2019    POINT (32.29810 2.75150)      1.057997
0          2015  POINT (28.61780 -20.17910)      0.996908
..          ...                         ...           ...
0          2016   POINT (39.75970 13.34270)      0.425004
0          2016   POINT (34.83250 -5.74410)      1.155177
0          2019   POINT (29.00060 -2.70070)      0.764184
0          2018  POINT (32.50810 -25.88280)      1.686300
0          2016    POINT (37.89500 7.24200)      0.759801

[492 rows x 3 columns]
```

[14]:
```
crs = CRS("EPSG:4326")
predicted_urban_wealth_df = gpd.GeoDataFrame(predicted_urban_wealth_df,
                                             geometry=predicted_urban_wealth_df['geometry
↪'],
                                             crs=crs)
true_urban_wealth_df = gpd.GeoDataFrame(true_urban_wealth_df,
                                        geometry=true_urban_wealth_df['geometry'],
                                        crs=crs)
```

Plot Predictions vs.Â Groundtruth

[15]:
```
divnorm=colors.TwoSlopeNorm(vmin=-4.5, vcenter=0., vmax=4.5)
# plt.subplots_adjust(wspace=None, hspace=None)
markersize=7
predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_urban_wealth_df.
↪COUNTRY_CODE)]

mosaic =  [['title_2012','title_2012','title_2012','title_2012','title_2012','title_2012
↪','.',
            'title_2013','title_2013','title_2013','title_2013','title_2013','title_2013
↪','.',
            'title_2014','title_2014','title_2014','title_2014','title_2014','title_2014
↪','.',
            'title_2015','title_2015','title_2015','title_2015','title_2015','title_2015
↪'],
        ['true2012','true2012','true2012','pred2012','pred2012','pred2012','.',
            'true2013', 'true2013','true2013','pred2013','pred2013','pred2013', '.',
            'true2014','true2014','true2014','pred2014','pred2014','pred2014','.',
        'true2015','true2015','true2015','pred2015','pred2015','pred2015'],
           ['title_2016','title_2016','title_2016','title_2016','title_2016','title_2016
↪','.',
            'title_2018','title_2018','title_2018','title_2018','title_2018','title_2018
↪','.',
            'title_2019','title_2019','title_2019','title_2019','title_2019','title_2019
↪','.',
            'title_2020','title_2020','title_2020','title_2020','title_2020','title_2020
↪'],
           ['true2016','true2016','true2016','pred2016','pred2016','pred2016', '.',
            'true2018','true2018','true2018', 'pred2018', 'pred2018','pred2018','.',
            'true2019','true2019','true2019','pred2019','pred2019','pred2019','.',
            'true2020', 'true2020', 'true2020','pred2020','pred2020','pred2020'],
]

fig, axes = plt.subplot_mosaic(mosaic,figsize=(10,6), gridspec_kw=(dict(height_ratios=(.
↪8,3,.8,3))))#, constrained_layout=True)
fig.suptitle('Vergleich der Vorhersagen und wahren Labels fÃ¼r das urbane Testset',
↪fontsize=16)

for index, row in enumerate(mosaic):
    row = [k for k in row if k!='.']
    keys=[]
    for k in row:
        if k not in keys:
            keys.append(k)
#     print(keys)
    for k in keys:
        predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_urban_
↪wealth_df[true_urban_wealth_df.SURVEY_YEAR==int(k[-4:])].COUNTRY_CODE)]
        if k.startswith('title'):
            if index==0:
                axes[k].set_title(k[-4:], fontsize=12,y=0)
```
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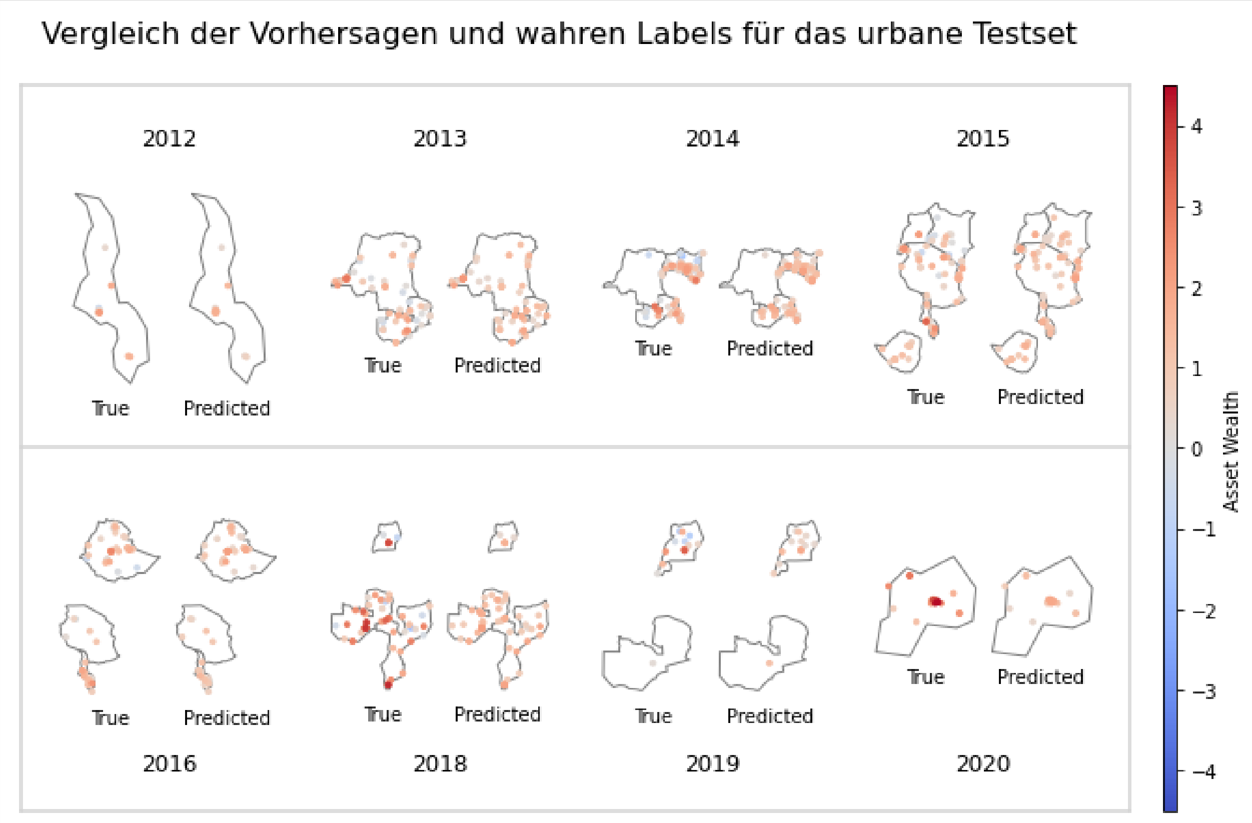
```
            else:
                axes[k].set_title(k[-4:], fontsize=12,y=-5.5)
        elif k.startswith('true'):
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            true_urban_wealth_df[true_urban_wealth_df.SURVEY_YEAR==int(k[-4:])].sort_
↪values(by='WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap='coolwarm',
↪norm=divnorm, markersize=markersize)
            axes[k].set_xlabel('True')
        else:
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            predicted_urban_wealth_df[predicted_urban_wealth_df.SURVEY_YEAR==int(k[-4:
↪])].sort_values(by='WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap=
↪'coolwarm',norm=divnorm, markersize=markersize)
            axes[k].set_xlabel('Predicted')
        axes[k].spines['top'].set_visible(False)
        axes[k].spines['right'].set_visible(False)
        axes[k].spines['bottom'].set_visible(False)
        axes[k].spines['left'].set_visible(False)
        axes[k].get_xaxis().set_ticks([])
        axes[k].get_yaxis().set_ticks([])

line = plt.Line2D([0.1,.925],[.45,.45], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[0,0], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[.9,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,0.1],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([.925,.925],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4.5, vmax=4.5), cmap='coolwarm')
cbaxes = fig.add_axes([0.95, 0,  0.01, 0.9])
cbar = fig.colorbar(sm, orientation='vertical',label='Asset Wealth',cax=cbaxes)

plt.show()
```



Rural Data

Get Label Data

[16]:
```
wealth_df = combine_wealth_dfs('/home/stoermer/Sentinel/gps_csv/')
```

[17]:
```
X_train_val, X_test, y_train_val, y_test = create_splits(img_dir='/mnt/datadisk/data/
↪VIIRS/preprocessed/asset/rural/all/', wealth_path='/home/stoermer/Sentinel/gps_csv/',␣
↪urban_rural='r', pre2015_path=False)
```

```
Gathering Label Data
```

```
100%|^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^
↪^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^
↪a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^
↪^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^^a-^| 5602/5602 [02:25<00:00,␣
↪38.55it/s]
```

[18]:
```
rural_test_labels = pd.DataFrame()
for x in tqdm(X_test):
    rural_test_labels = pd.concat([rural_test_labels, get_label_for_img(wealth_df, x)])
rural_test_labels
```

```
  0%|          | 0/1121 [00:00<?, ?it/s]
```

```
[18]:    WEALTH_INDEX  SURVEY_YEAR    LATNUM  LONGNUM
0      -0.688140         2015  -17.7214  31.7259
0      -0.216390         2014   -0.6815  35.2460
0      -0.112214         2016    7.2301  35.3157
0      -0.212770         2015  -12.9103  34.2767
0      -0.168055         2016   -8.4875  39.2632
..           ...          ...       ...      ...
0      -0.734604         2014    1.9172  33.6136
0      -0.500560         2015   -1.7555  29.6134
0      -0.504263         2015  -16.4775  30.4724
0      -0.375565         2014    0.0005  37.9925
0      -0.537768         2015   -4.4555  39.2872

[1121 rows x 4 columns]
```

Get Predictions of Best Model

```
[19]: model = keras.models.load_model('./resnet50_r_viirs.h5')
```

```
[20]: data_rural = np.zeros(shape=(len(X_test), 3, 1000, 1000))
for index, img in tqdm(enumerate(X_test)):
    # Read in each Image
    with rasterio.open(os.path.join(viirs_path, img)) as i:
        array = i.read().astype("float32")

    # Ensure that the Array is not empty
    array[np.isnan(array)] = 0
    assert not np.any(np.isnan(array)), "Float"

    # Add to batch
    data_rural[index] = array

    # Check if batch is already full (Note: Index in batch array is from 0...4 hence we␣
↪need to add +1 to batch_ele)
data_rural = data_rural.transpose(0, 2, 3, 1)
preds_rural = model.predict(data_rural)
len(preds_rural)
```

```
0it [00:00, ?it/s]
```

```
[20]: 1121
```

Create Geo DataFrames for Groundtruth and Predictions

[21]:
```
crs = CRS("EPSG:4326")
geometry = gpd.points_from_xy(rural_test_labels.LONGNUM, rural_test_labels.LATNUM)

true_rural_wealth_df = gpd.GeoDataFrame(rural_test_labels,
                        geometry=geometry,
                        crs=crs
                       )
true_rural_wealth_df['COUNTRY_CODE'] = [x.split('_')[3] for x in X_test]
true_rural_wealth_df = true_rural_wealth_df[['SURVEY_YEAR', 'geometry', 'COUNTRY_CODE',
↪'WEALTH_INDEX']]
true_rural_wealth_df.head(3)
```

[21]:
```
   SURVEY_YEAR                     geometry COUNTRY_CODE  WEALTH_INDEX
0         2015  POINT (31.72590 -17.72140)          ZWE     -0.688140
0         2014   POINT (35.24600 -0.68150)          KEN     -0.216390
0         2016    POINT (35.31570 7.23010)          ETH     -0.112214
```

[22]:
```
predicted_rural_wealth_df = true_rural_wealth_df.loc[:,['SURVEY_YEAR', 'geometry',
↪'COUNTRY_CODE']]
predicted_rural_wealth_df['WEALTH_INDEX'] = preds_rural
predicted_rural_wealth_df.head(3)
```

[22]:
```
   SURVEY_YEAR                     geometry COUNTRY_CODE  WEALTH_INDEX
0         2015  POINT (31.72590 -17.72140)          ZWE     -0.548155
0         2014   POINT (35.24600 -0.68150)          KEN     -0.588530
0         2016    POINT (35.31570 7.23010)          ETH     -0.588530
```

Plot Predictions vs.Â Groundtruth

[23]:
```
divnorm=colors.TwoSlopeNorm(vmin=-4.5, vcenter=0., vmax=4.5)
# plt.subplots_adjust(wspace=None, hspace=None)
markersize=7
predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_rural_wealth_df.
↪COUNTRY_CODE)]

mosaic =  [['title_2012','title_2012','title_2012','title_2012','title_2012','title_2012
↪','.',
            'title_2013','title_2013','title_2013','title_2013','title_2013','title_2013
↪','.',
            'title_2014','title_2014','title_2014','title_2014','title_2014','title_2014
↪','.',
            'title_2015','title_2015','title_2015','title_2015','title_2015','title_2015
↪'],
        ['true2012','true2012','true2012','pred2012','pred2012','pred2012','.',
            'true2013', 'true2013','true2013','pred2013','pred2013','pred2013', '.',
            'true2014','true2014','true2014','pred2014','pred2014','pred2014','.',
        'true2015','true2015','true2015','pred2015','pred2015','pred2015'],
           ['title_2016','title_2016','title_2016','title_2016','title_2016','title_2016
↪','.',
            'title_2018','title_2018','title_2018','title_2018','title_2018','title_2018
↪','.',
```

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```
            'title_2019','title_2019','title_2019','title_2019','title_2019','title_2019
↪','.',
            'title_2020','title_2020','title_2020','title_2020','title_2020','title_2020
↪'],
           ['true2016','true2016','true2016','pred2016','pred2016','pred2016', '.',
            'true2018','true2018','true2018', 'pred2018', 'pred2018','pred2018','.',
            'true2019','true2019','true2019','pred2019','pred2019','pred2019','.',
            'true2020', 'true2020', 'true2020','pred2020','pred2020','pred2020'],
]

fig, axes = plt.subplot_mosaic(mosaic,figsize=(10,6), gridspec_kw=(dict(height_ratios=(.
↪8,3,.8,3))))#, constrained_layout=True)
fig.suptitle('Vergleich der Vorhersagen und wahren Labels fÃ¼r das rurale Testset',
↪fontsize=16)

for index, row in enumerate(mosaic):
    row = [k for k in row if k!='.']
    keys=[]
    for k in row:
        if k not in keys:
            keys.append(k)
#     print(keys)
    for k in keys:
        predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_rural_
↪wealth_df[true_rural_wealth_df.SURVEY_YEAR==int(k[-4:])].COUNTRY_CODE)]
        if k.startswith('title'):
            if index==0:
                axes[k].set_title(k[-4:], fontsize=12,y=0)
            else:
                axes[k].set_title(k[-4:], fontsize=12,y=-5.5)
        elif k.startswith('true'):
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            true_rural_wealth_df[true_rural_wealth_df.SURVEY_YEAR==int(k[-4:])].sort_
↪values(by='WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap='coolwarm',
↪norm=divnorm, markersize=markersize)
            axes[k].set_xlabel('True')
        else:
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            predicted_rural_wealth_df[predicted_rural_wealth_df.SURVEY_YEAR==int(k[-4:
↪])].sort_values(by='WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap=
↪'coolwarm',norm=divnorm, markersize=markersize)
            axes[k].set_xlabel('Predicted')
        axes[k].spines['top'].set_visible(False)
        axes[k].spines['right'].set_visible(False)
        axes[k].spines['bottom'].set_visible(False)
        axes[k].spines['left'].set_visible(False)
        axes[k].get_xaxis().set_ticks([])
        axes[k].get_yaxis().set_ticks([])

line = plt.Line2D([0.1,.925],[.45,.45], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[0,0], transform=fig.transFigure, color="lightgrey")
```

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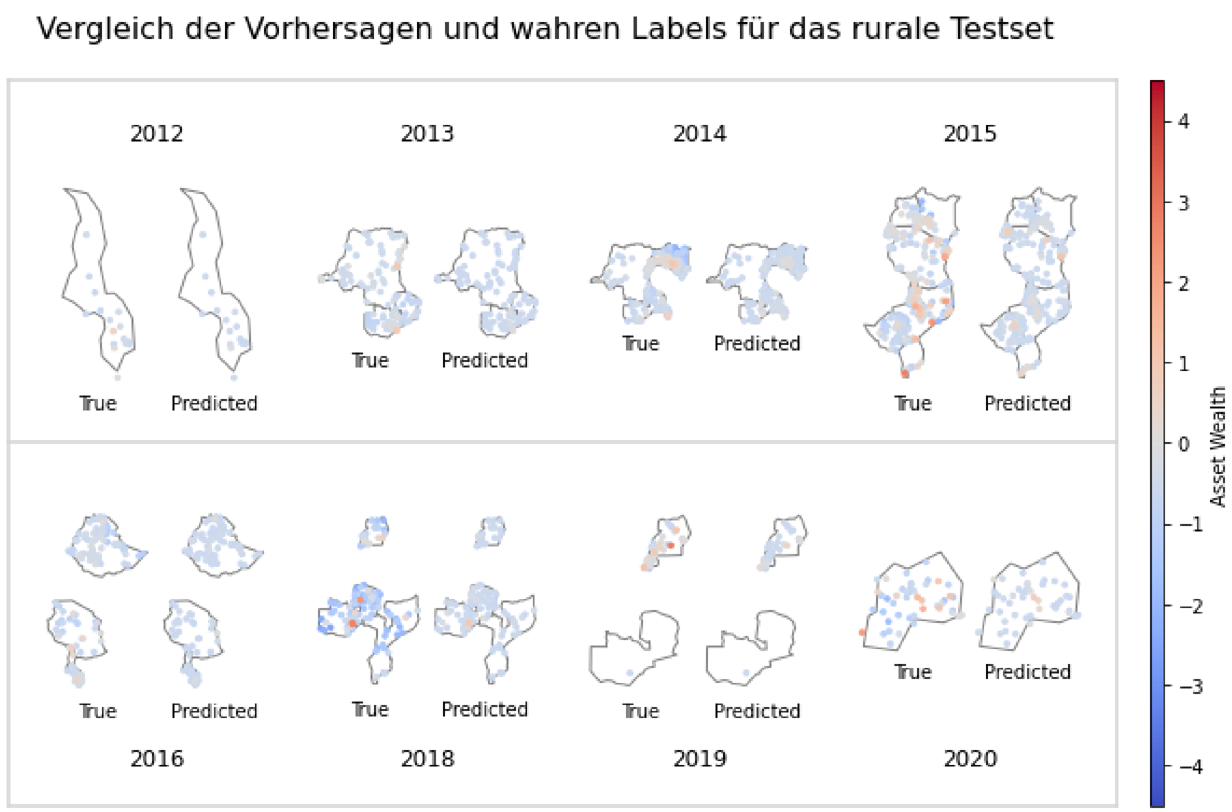
```
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[.9,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,0.1],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([.925,.925],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4.5, vmax=4.5), cmap='coolwarm')
cbaxes = fig.add_axes([0.95, 0,  0.01, 0.9])
cbar = fig.colorbar(sm, orientation='vertical',label='Asset Wealth',cax=cbaxes)

plt.show()
```



Combine rural and urban predictions and labels

[24]:
```
predicted_wealth_df = pd.concat([predicted_rural_wealth_df,predicted_urban_wealth_df])
true_wealth_df = pd.concat([true_rural_wealth_df, true_urban_wealth_df])
```

Plot all predictions

[25]:
```
divnorm=colors.TwoSlopeNorm(vmin=-4.5, vcenter=0., vmax=4.5)
markersize=5
predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_rural_wealth_df.
↪COUNTRY_CODE)]

mosaic =  [['title_2012','title_2012','title_2012','title_2012','title_2012','title_2012
↪','.',
            'title_2013','title_2013','title_2013','title_2013','title_2013','title_2013
↪','.',
            'title_2014','title_2014','title_2014','title_2014','title_2014','title_2014
↪','.',
            'title_2015','title_2015','title_2015','title_2015','title_2015','title_2015
↪'],
        ['true2012','true2012','true2012','pred2012','pred2012','pred2012','.',
            'true2013', 'true2013','true2013','pred2013','pred2013','pred2013', '.',
            'true2014','true2014','true2014','pred2014','pred2014','pred2014','.',
        'true2015','true2015','true2015','pred2015','pred2015','pred2015'],
           ['title_2016','title_2016','title_2016','title_2016','title_2016','title_2016
↪','.',
            'title_2018','title_2018','title_2018','title_2018','title_2018','title_2018
↪','.',
            'title_2019','title_2019','title_2019','title_2019','title_2019','title_2019
↪','.',
            'title_2020','title_2020','title_2020','title_2020','title_2020','title_2020
↪'],
           ['true2016','true2016','true2016','pred2016','pred2016','pred2016', '.',
            'true2018','true2018','true2018', 'pred2018', 'pred2018','pred2018','.',
            'true2019','true2019','true2019','pred2019','pred2019','pred2019','.',
            'true2020', 'true2020', 'true2020','pred2020','pred2020','pred2020'],
]

fig, axes = plt.subplot_mosaic(mosaic,figsize=(10,6), gridspec_kw=(dict(height_ratios=(.
↪8,3,.8,3))))#, constrained_layout=True)
fig.suptitle('Vergleich der Vorhersagen und wahren Labels fÃ¼r das rurale Testset',
↪fontsize=16)

for index, row in enumerate(mosaic):
    row = [k for k in row if k!='.']
    keys=[]
    for k in row:
        if k not in keys:
            keys.append(k)

    for k in keys:
```

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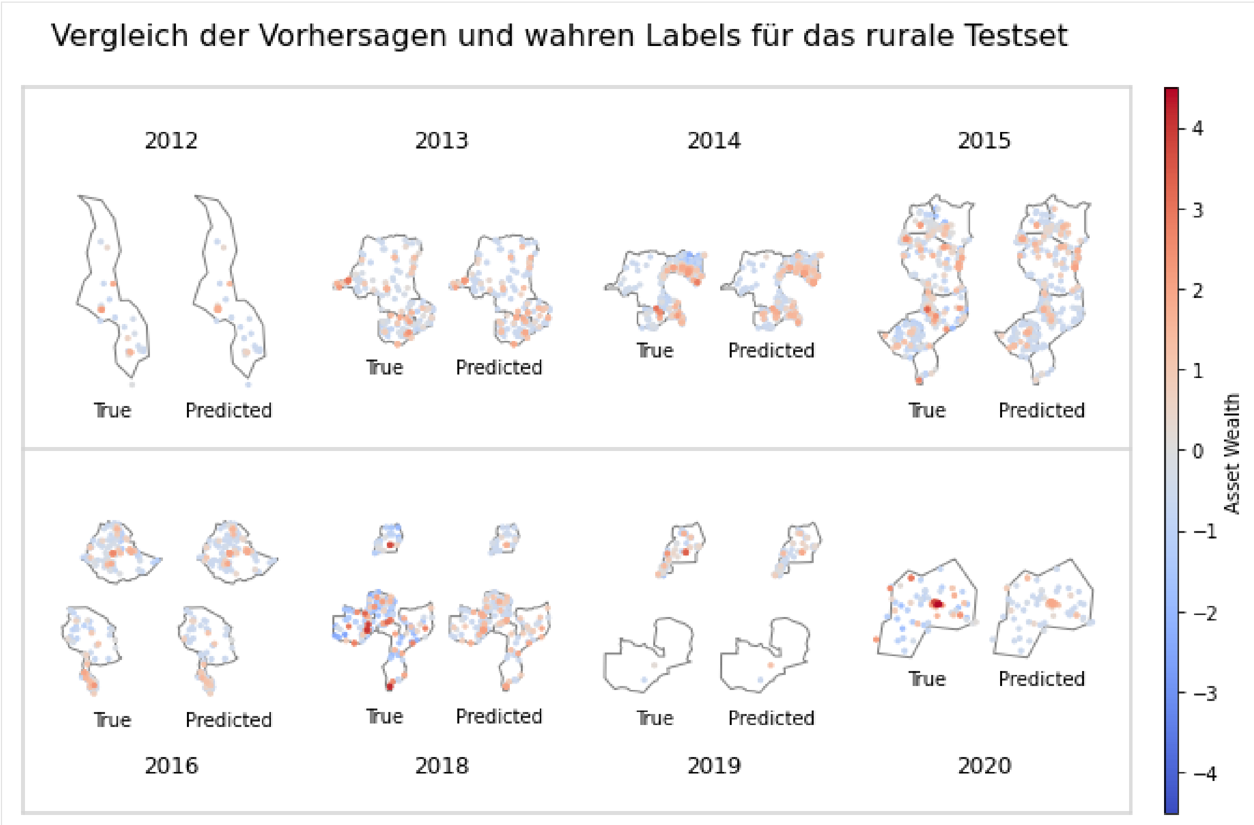
```
        predicted_countries_gdf = countries_gdf[countries_gdf.iso_a3.isin(true_wealth_
↪df[true_wealth_df.SURVEY_YEAR==int(k[-4:])].COUNTRY_CODE)]
        if k.startswith('title'):
            if index==0:
                axes[k].set_title(k[-4:], fontsize=12,y=0)
            else:
                axes[k].set_title(k[-4:], fontsize=12,y=-5.5)
        elif k.startswith('true'):
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            true_wealth_df[true_wealth_df.SURVEY_YEAR==int(k[-4:])].sort_values(by=
↪'WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap='coolwarm',norm=divnorm,
↪ markersize=markersize)
            axes[k].set_xlabel('True')
        else:
            predicted_countries_gdf.plot(ax=axes[k], color='white', edgecolor='grey')
            predicted_wealth_df[predicted_wealth_df.SURVEY_YEAR==int(k[-4:])].sort_
↪values(by='WEALTH_INDEX').plot(ax = axes[k], column='WEALTH_INDEX', cmap='coolwarm',
↪norm=divnorm, markersize=markersize)
            axes[k].set_xlabel('Predicted')
        axes[k].spines['top'].set_visible(False)
        axes[k].spines['right'].set_visible(False)
        axes[k].spines['bottom'].set_visible(False)
        axes[k].spines['left'].set_visible(False)
        axes[k].get_xaxis().set_ticks([])
        axes[k].get_yaxis().set_ticks([])

line = plt.Line2D([0.1,.925],[.45,.45], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[0,0], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,.925],[.9,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([0.1,0.1],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)
line = plt.Line2D([.925,.925],[0,.9], transform=fig.transFigure, color="lightgrey")
fig.add_artist(line)

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4.5, vmax=4.5), cmap='coolwarm')
cbaxes = fig.add_axes([0.95, 0,  0.01, 0.9])
cbar = fig.colorbar(sm, orientation='vertical',label='Asset Wealth',cax=cbaxes)

plt.show()
```



Get r2 Score for best Models

[13]:
```
from sklearn.metrics import mean_squared_error, r2_score


urban_r2_score = r2_score(true_urban_wealth_df.WEALTH_INDEX, predicted_urban_wealth_df.
↪WEALTH_INDEX)
rural_r2_score = r2_score(true_rural_wealth_df.WEALTH_INDEX, predicted_rural_wealth_df.
↪WEALTH_INDEX)

print(urban_r2_score)
rural_r2_score
```

```
0.32608796277450536
```

[13]:
```
0.14404635936378374
```

Save Predictions and Groundtruth

[26]:
```
predicted_urban_wealth_df.to_csv('./predicted_urban_wealth_df.csv')
true_urban_wealth_df.to_csv('./true_urban_wealth_df.csv')

predicted_rural_wealth_df.to_csv('./predicted_rural_wealth_df.csv')
true_rural_wealth_df.to_csv('./true_rural_wealth_df.csv')
```

[6]:
```
predicted_urban_wealth_df = pd.read_csv('./predicted_urban_wealth_df.csv')[['SURVEY_YEAR
↪','geometry', 'WEALTH_INDEX']]
predicted_urban_wealth_df = gpd.GeoDataFrame(predicted_urban_wealth_df.loc[:, [c for c␣
↪in predicted_urban_wealth_df.columns if c != "geometry"]],
                                             geometry=gpd.GeoSeries.from_wkt(predicted_
↪urban_wealth_df["geometry"]),
                                             crs=crs,
                                            )

true_urban_wealth_df = pd.read_csv('./true_urban_wealth_df.csv')[['SURVEY_YEAR','geometry
↪','COUNTRY_CODE', 'WEALTH_INDEX']]
true_urban_wealth_df = gpd.GeoDataFrame(true_urban_wealth_df.loc[:, [c for c in true_
↪urban_wealth_df.columns if c != "geometry"]],
                                        geometry=gpd.GeoSeries.from_wkt(true_urban_
↪wealth_df["geometry"]),
                                        crs=crs,
                                       )


predicted_rural_wealth_df = pd.read_csv('./predicted_rural_wealth_df.csv')[['SURVEY_YEAR
↪','geometry', 'WEALTH_INDEX']]
predicted_rural_wealth_df = gpd.GeoDataFrame(predicted_rural_wealth_df.loc[:, [c for c␣
↪in predicted_rural_wealth_df.columns if c != "geometry"]],
                                             geometry=gpd.GeoSeries.from_wkt(predicted_
↪rural_wealth_df["geometry"]),
                                             crs=crs,
                                            )

true_rural_wealth_df = pd.read_csv('./true_rural_wealth_df.csv')[['SURVEY_YEAR','geometry
↪','COUNTRY_CODE', 'WEALTH_INDEX']]
true_rural_wealth_df = gpd.GeoDataFrame(true_rural_wealth_df.loc[:, [c for c in true_
↪rural_wealth_df.columns if c != "geometry"]],
                                        geometry=gpd.GeoSeries.from_wkt(true_rural_
↪wealth_df["geometry"]),
                                        crs=crs,
                                       )
```

Predict Asset Wealth for Mozambique

Load general geographic Data of Mozambique

```
[28]: world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
      moz = world[world.name=='Mozambique']
```

Load Mozambique Survey Data

```
[29]: moz_df = pd.read_csv('./moz_2016_2021.csv')
      moz_df = moz_df[['URBAN_RURA', 'LATNUM', 'LONGNUM', 'SURVEY_YEAR', 'Filename']]
      print(moz_df.shape)
      moz_df.head(3)
```

```
(2635, 5)
```

```
[29]:    URBAN_RURA    LATNUM  LONGNUM  SURVEY_YEAR  \
      0           0 -13.2856  35.2311         2016
      1           0 -13.3226  35.2552         2016
      2           0 -13.2716  35.1965         2016

                                           Filename
      0  -13.2856_35.2311_20160101-20161231_MOZ_u_2.0.tif
      1  -13.3226_35.2552_20160101-20161231_MOZ_u_2.0.tif
      2  -13.2716_35.1965_20160101-20161231_MOZ_u_2.0.tif
```

Urban

Load Data for Mozambique 2016, 2017, 2019, 2020 and 2021

```
[30]: model = keras.models.load_model('./vgg19_viirs_s2_u.h5')
```

```
[31]: moz_path_urban = '/mnt/datadisk/data/VIIRS_Sentinel2/asset/urban/mozambique_2016_2021'
      moz_list_urban = os.listdir(moz_path_urban)
      len(moz_list_urban)
```

```
[31]: 1115
```

```
[32]: moz_2016_urban = [i for i in moz_list_urban if '2016' in i]
      moz_2017_urban = [i for i in moz_list_urban if '2017' in i]
      moz_2019_urban = [i for i in moz_list_urban if '2019' in i]
      moz_2020_urban = [i for i in moz_list_urban if '2020' in i]
      moz_2021_urban = [i for i in moz_list_urban if '2021' in i]
```

```
[33]: data_urban = {}
      for moz_data_urban in [[moz_2016_urban,'2016'],[moz_2017_urban,'2017'],[moz_2019_urban,
      ↪'2019'],[moz_2020_urban,'2020'],[moz_2021_urban,'2021']]:
          data_urban[moz_data_urban[1]] = np.zeros(shape=(len(moz_data_urban[0]), 14, 200,␣
      ↪200))
          for index, img in tqdm(enumerate(moz_data_urban[0])):
```

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```
        # Read in each Image
        with rasterio.open(os.path.join(moz_path_urban, img)) as i:
            array = i.read().astype("float32")

        # Ensure that the Array is not empty
        array[np.isnan(array)] = 0
        assert not np.any(np.isnan(array)), "Float"

        data_urban[moz_data_urban[1]][index] = array

    data_urban[moz_data_urban[1]] = data_urban[moz_data_urban[1]].transpose(0, 2, 3, 1)
    assert len(data_urban[moz_data_urban[1]]) == len(moz_data_urban[0])
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

Predict Asset Wealth

[34]:

```
preds_urban = {}
for year in tqdm(data_urban.keys()):
    preds_urban[year] = model.predict(data_urban[year])
print(preds_urban.keys())
len(preds_urban['2016'])
```

```
  0%|          | 0/5 [00:00<?, ?it/s]
```

```
dict_keys(['2016', '2017', '2019', '2020', '2021'])
```

[34]:

```
223
```

[35]:

```
pred_file_urban_dict = {'Filename':moz_2016_urban+moz_2017_urban+moz_2019_urban+moz_2020_
↪urban+moz_2021_urban,
                 'Prediction':[pred[0] for pred in preds_urban['2016']]+
                 [pred[0] for pred in preds_urban['2017']]+
                 [pred[0] for pred in preds_urban['2019']]+
                 [pred[0] for pred in preds_urban['2020']]+
                 [pred[0] for pred in preds_urban['2021']]}
pred_file_urban_df = pd.DataFrame(pred_file_urban_dict)
print(pred_file_urban_df.shape)
pred_file_urban_df.head(3)
```

```
(1115, 2)
```

[35]:

	Filename	Prediction
0	-25.9443_32.6146_20160101-20161231_MOZ_u_2.0.tif	1.961596
1	-25.9002_32.6141_20160101-20161231_MOZ_u_2.0.tif	1.722382
2	-23.7538_35.3463_20160101-20161231_MOZ_u_2.0.tif	1.993611

Merge Predictions with Survey Data

[36]:
```
asset_pred_urban_df = moz_df.merge(pred_file_urban_df)
print(asset_pred_urban_df.shape)
asset_pred_urban_df.head(3)
```

```
(1115, 6)
```

[36]:
```
   URBAN_RURA   LATNUM  LONGNUM  SURVEY_YEAR  \
0           0 -13.2856  35.2311         2016
1           0 -13.3226  35.2552         2016
2           0 -13.2716  35.1965         2016

                                          Filename  Prediction
0  -13.2856_35.2311_20160101-20161231_MOZ_u_2.0.tif    1.521431
1  -13.3226_35.2552_20160101-20161231_MOZ_u_2.0.tif    1.153307
2  -13.2716_35.1965_20160101-20161231_MOZ_u_2.0.tif    1.414657
```

Merge Predictions with Survey Data

[37]:
```
geometry = gpd.points_from_xy(asset_pred_urban_df.LONGNUM, asset_pred_urban_df.LATNUM)
```

[38]:
```
asset_pred_urban_df = gpd.GeoDataFrame(asset_pred_urban_df,
                                        geometry=geometry,
                                        crs=crs
                                       )
asset_pred_urban_df = asset_pred_urban_df[['SURVEY_YEAR', 'geometry', 'Prediction']]
print(asset_pred_urban_df.shape)
asset_pred_urban_df.head(3)
```

```
(1115, 3)
```

[38]:
```
   SURVEY_YEAR                    geometry  Prediction
0         2016  POINT (35.23110 -13.28560)    1.521431
1         2016  POINT (35.25520 -13.32260)    1.153307
2         2016  POINT (35.19650 -13.27160)    1.414657
```

[39]:
```
urban_2016_df = asset_pred_urban_df[asset_pred_urban_df.SURVEY_YEAR==2016]
urban_2016_df.shape

urban_2017_df = asset_pred_urban_df[asset_pred_urban_df.SURVEY_YEAR==2017]
urban_2017_df.shape

urban_2019_df = asset_pred_urban_df[asset_pred_urban_df.SURVEY_YEAR==2019]
urban_2019_df.shape

urban_2020_df = asset_pred_urban_df[asset_pred_urban_df.SURVEY_YEAR==2020]
urban_2020_df.shape

urban_2021_df = asset_pred_urban_df[asset_pred_urban_df.SURVEY_YEAR==2021]
urban_2021_df.shape
```

[39]:
```
(223, 3)
```

[40]:
```
fig, axes = plt.subplots(1, 5, sharey=True,constrained_layout=True, figsize=(12,9))


from matplotlib import colors

divnorm=colors.TwoSlopeNorm(vmin=-4, vcenter=0, vmax=4)
markersize=5
subplot_title_size = 16

axes[0].set_aspect('equal')
plt.suptitle('Asset Wealth Verteilung der besten Modelle fÃ¼r Mosambik', fontsize=26, y=.
↪8, x=0.53)

moz.plot(ax=axes[0], color='white', edgecolor='grey')

urban_2016_df.sort_values(by='Prediction').plot(ax = axes[0], column='Prediction',
                  cmap='coolwarm', norm=divnorm, markersize=markersize)


axes[0].set_xlabel('Latitude', fontsize=13)
axes[0].set_ylabel('Longitude', fontsize=13)
axes[0].set_title('Mosambik 2016', fontsize=subplot_title_size)
axes[0].set_aspect('equal')

moz.plot(ax=axes[1], color='white', edgecolor='grey')
urban_2017_df.sort_values(by='Prediction').plot(ax = axes[1], column='Prediction',
                  cmap='coolwarm', norm=divnorm, markersize=markersize)


axes[1].set_xlabel('Latitude', fontsize=13)
axes[1].set_title('Mosambik 2017', fontsize=subplot_title_size)

axes[1].set_aspect('equal')

moz.plot(ax=axes[2], color='white', edgecolor='grey')
urban_2019_df.sort_values(by='Prediction').plot(ax = axes[2], column='Prediction',
                  cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[2].set_xlabel('Latitude', fontsize=13)
axes[2].set_title('Mosambik 2019', fontsize=subplot_title_size)
axes[2].set_aspect('equal')

moz.plot(ax=axes[3], color='white', edgecolor='grey')
urban_2020_df.sort_values(by='Prediction').plot(ax = axes[3], column='Prediction',
                  cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[3].set_xlabel('Latitude', fontsize=13)
axes[3].set_title('Mosambik 2020', fontsize=subplot_title_size)
axes[3].set_aspect('equal')

moz.plot(ax=axes[4], color='white', edgecolor='grey')
urban_2021_df.sort_values(by='Prediction').plot(ax = axes[4], column='Prediction',
```

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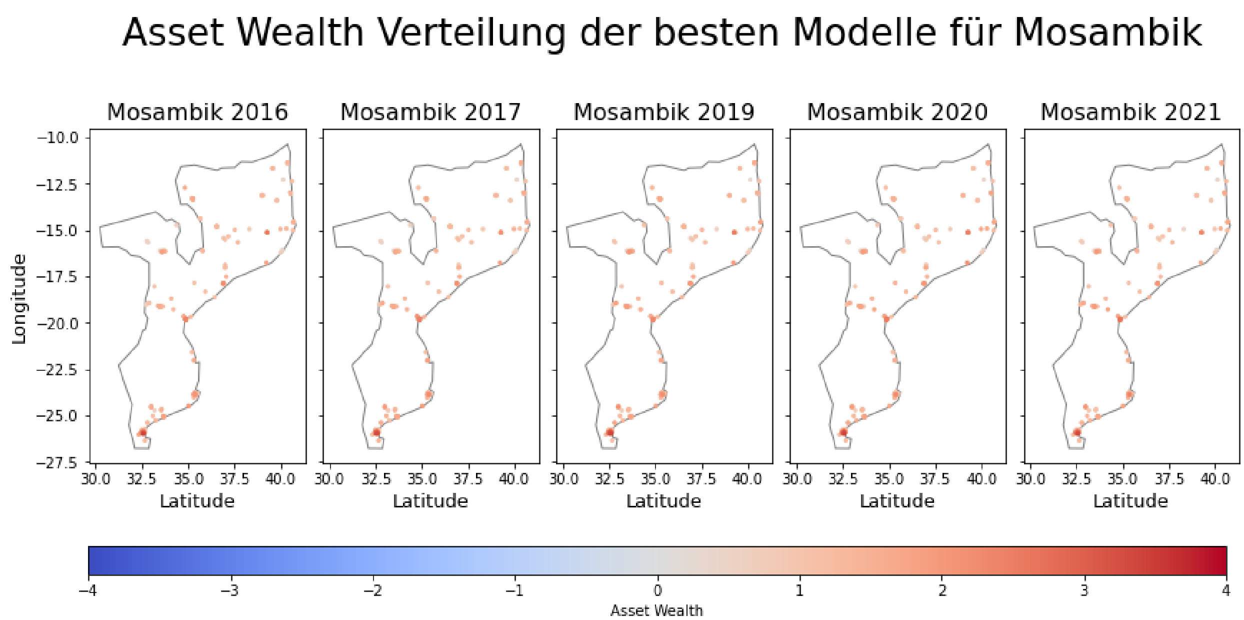
```
                        cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[4].set_xlabel('Latitude', fontsize=13)
axes[4].set_title('Mosambik 2021', fontsize=subplot_title_size)
axes[4].set_aspect('equal')

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4, vmax=4), cmap='coolwarm')
cbaxes = fig.add_axes([0.066, 0.2, .92, 0.03])
cbar = fig.colorbar(sm, orientation='horizontal',label='Asset Wealth',cax=cbaxes)


plt.show()
```



Rural

Load Data for Mozambique 2016, 2017, 2019, 2020 and 2021

[41]:
```
model = keras.models.load_model('./resnet50_r_viirs.h5')
```

[42]:
```
moz_path_rural = '/mnt/datadisk/data/VIIRS/preprocessed/asset/rural/mozambique_2016_2021/
↪prep'

moz_rural = os.listdir(moz_path_rural)
len(moz_rural)
```

[42]:
```
1520
```

[43]:
```
moz_2016_rural = [i for i in moz_rural if '2016' in i]
moz_2017_rural = [i for i in moz_rural if '2017' in i]
moz_2019_rural = [i for i in moz_rural if '2019' in i]
moz_2020_rural = [i for i in moz_rural if '2020' in i]
```

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```
moz_2021_rural = [i for i in moz_rural if '2021' in i]
```

[44]:
```
data_rural= {}
for moz_data_rural in [[moz_2016_rural,'2016'],[moz_2017_rural,'2017'],[moz_2019_rural,
↪'2019'],[moz_2020_rural,'2020'],[moz_2021_rural,'2021']]:
    data_rural[moz_data_rural[1]] = np.zeros(shape=(len(moz_data_rural[0]), 3, 1000,␣
↪1000))
    for index, img in tqdm(enumerate(moz_data_rural[0])):
        # Read in each Image
        with rasterio.open(os.path.join(moz_path_rural, img)) as i:
            array = i.read().astype("float32")

        # Ensure that the Array is not empty
        array[np.isnan(array)] = 0
        assert not np.any(np.isnan(array)), "Float"

        # Add to batch
        data_rural[moz_data_rural[1]][index] = array

        # Check if batch is already full (Note: Index in batch array is from 0...4 hence␣
↪we need to add +1 to batch_ele)
    data_rural[moz_data_rural[1]] = data_rural[moz_data_rural[1]].transpose(0, 2, 3, 1)
    assert len(data_rural[moz_data_rural[1]]) == len(moz_data_rural[0])
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

```
0it [00:00, ?it/s]
```

Predict Asset Wealth

[45]:
```
from tensorflow.keras import optimizers, models
preds_rural = {}
for year in tqdm(data_rural.keys()):
    preds_rural[year] = model.predict(data_rural[year])
print(preds_rural.keys())
len(preds_rural['2016'])
```

```
  0%|          | 0/5 [00:00<?, ?it/s]
```

```
dict_keys(['2016', '2017', '2019', '2020', '2021'])
```

[45]:
```
304
```

[46]:
```
pred_rural_file_dict = {'Filename':
                        moz_2016_rural+
                        moz_2017_rural+
                        moz_2019_rural+
```

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```
                         moz_2020_rural+
                         moz_2021_rural,
                         'Prediction':
                         [pred[0] for pred in preds_rural['2016']]+
                         [pred[0] for pred in preds_rural['2017']]+
                         [pred[0] for pred in preds_rural['2019']]+
                         [pred[0] for pred in preds_rural['2020']]+
                         [pred[0] for pred in preds_rural['2021']]}
pred_rural_file_df = pd.DataFrame(pred_rural_file_dict)
print(pred_rural_file_df.shape)
pred_rural_file_df.head(3)
```

```
(1520, 2)
```

[46]:
```
                                              Filename  Prediction
0  -20.5253_34.0313_20160101-20161231_MOZ_r_10.0.tif   -0.588530
1  -14.4227_38.3001_20160101-20161231_MOZ_r_10.0.tif   -0.469308
2  -15.8257_38.5071_20160101-20161231_MOZ_r_10.0.tif   -0.588530
```

Merge Predictions with Survey Data

[47]:
```
asset_pred_rural_df = moz_df.merge(pred_rural_file_df)
print(asset_pred_rural_df.shape)
asset_pred_rural_df.head(3)
```

```
(1520, 6)
```

[47]:
```
   URBAN_RURA   LATNUM  LONGNUM  SURVEY_YEAR  \
0           1 -15.1365  36.5967         2016
1           1 -14.6769  36.4565         2016
2           1 -12.0948  34.8491         2016

                                              Filename  Prediction
0  -15.1365_36.5967_20160101-20161231_MOZ_r_10.0.tif   -0.266213
1  -14.6769_36.4565_20160101-20161231_MOZ_r_10.0.tif   -0.588530
2  -12.0948_34.8491_20160101-20161231_MOZ_r_10.0.tif   -0.588530
```

Get Geocoordinates and create Geometry Objects

Merge Predictions with Survey Data

[48]:
```
geometry = gpd.points_from_xy(asset_pred_rural_df.LONGNUM, asset_pred_rural_df.LATNUM)
```

[49]:
```
asset_pred_rural_df = gpd.GeoDataFrame(asset_pred_rural_df,
                        geometry=geometry,
                        crs=crs
                       )
asset_pred_rural_df = asset_pred_rural_df[['SURVEY_YEAR', 'geometry', 'Prediction']]
print(asset_pred_rural_df.shape)
asset_pred_rural_df.head(3)
```

```
(1520, 3)
```

[49]:

```
   SURVEY_YEAR                    geometry  Prediction
0         2016  POINT (36.59670 -15.13650)   -0.266213
1         2016  POINT (36.45650 -14.67690)   -0.588530
2         2016  POINT (34.84910 -12.09480)   -0.588530
```

[50]:

```
asset_pred_rural_df.to_csv('./moz_rural_asset_wealth_prediction.csv')
```

[51]:

```
rural_2016_df = asset_pred_rural_df[asset_pred_rural_df.SURVEY_YEAR==2016]
rural_2016_df.shape

rural_2017_df = asset_pred_rural_df[asset_pred_rural_df.SURVEY_YEAR==2017]
rural_2017_df.shape

rural_2019_df = asset_pred_rural_df[asset_pred_rural_df.SURVEY_YEAR==2019]
rural_2019_df.shape

rural_2020_df = asset_pred_rural_df[asset_pred_rural_df.SURVEY_YEAR==2020]
rural_2020_df.shape

rural_2021_df = asset_pred_rural_df[asset_pred_rural_df.SURVEY_YEAR==2021]
rural_2021_df.shape
```

[51]:

```
(304, 3)
```

[52]:

```
fig, axes = plt.subplots(1, 5, sharey=True,constrained_layout=True, figsize=(12,9))


from matplotlib import colors

divnorm=colors.TwoSlopeNorm(vmin=-4, vcenter=0, vmax=4)
markersize=5
subplot_title_size = 16

axes[0].set_aspect('equal')
plt.suptitle('Asset Wealth Verteilung der besten Modelle fÃ¼r Mosambik', fontsize=26, y=.
↪8, x=0.53)

moz.plot(ax=axes[0], color='white', edgecolor='grey')
rural_2016_df.sort_values(by='Prediction').plot(ax = axes[0], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)

axes[0].set_xlabel('Latitude', fontsize=13)
axes[0].set_ylabel('Longitude', fontsize=13)
axes[0].set_title('Mosambik 2016', fontsize=subplot_title_size)
axes[0].set_aspect('equal')

moz.plot(ax=axes[1], color='white', edgecolor='grey')
rural_2017_df.sort_values(by='Prediction').plot(ax = axes[1], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[1].set_xlabel('Latitude', fontsize=13)
axes[1].set_title('Mosambik 2017', fontsize=subplot_title_size)
```

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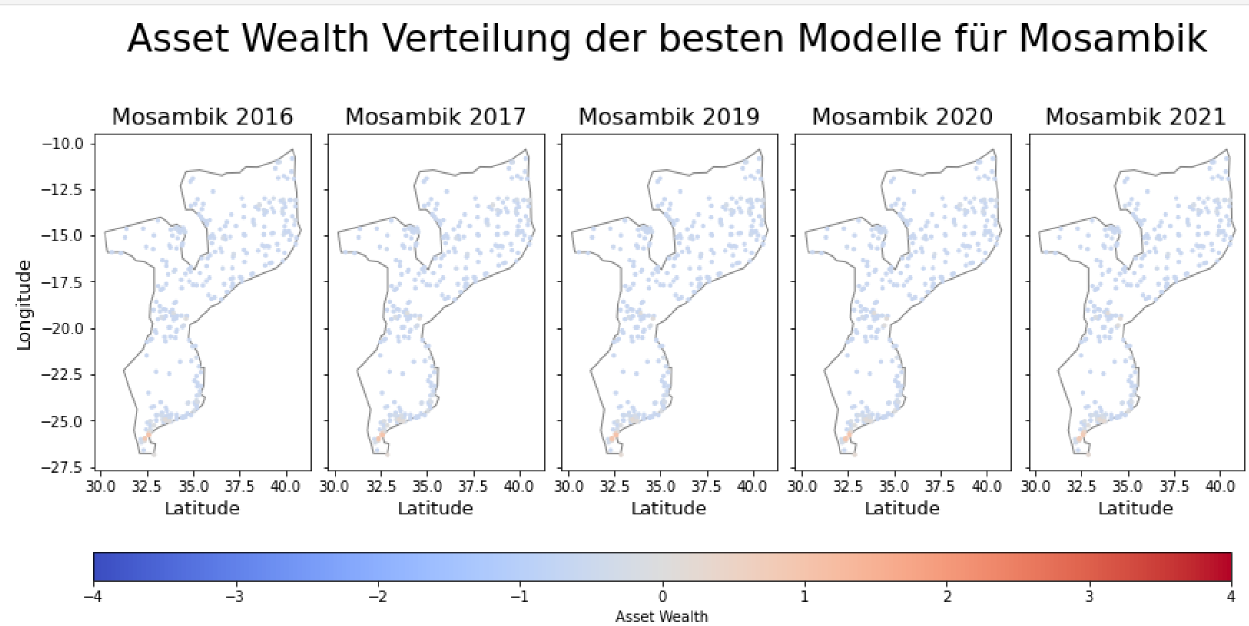
```
axes[1].set_aspect('equal')

moz.plot(ax=axes[2], color='white', edgecolor='grey')
rural_2019_df.sort_values(by='Prediction').plot(ax = axes[2], column='Prediction',
                cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[2].set_xlabel('Latitude', fontsize=13)
axes[2].set_title('Mosambik 2019', fontsize=subplot_title_size)
axes[2].set_aspect('equal')

moz.plot(ax=axes[3], color='white', edgecolor='grey')
rural_2020_df.sort_values(by='Prediction').plot(ax = axes[3], column='Prediction',
                cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[3].set_xlabel('Latitude', fontsize=13)
axes[3].set_title('Mosambik 2020', fontsize=subplot_title_size)
axes[3].set_aspect('equal')

moz.plot(ax=axes[4], color='white', edgecolor='grey')
rural_2021_df.sort_values(by='Prediction').plot(ax = axes[4], column='Prediction',
                cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[4].set_xlabel('Latitude', fontsize=13)
axes[4].set_title('Mosambik 2021', fontsize=subplot_title_size)
axes[4].set_aspect('equal')

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4, vmax=4), cmap='coolwarm')
cbaxes = fig.add_axes([0.066, 0.2, .92, 0.03])
cbar = fig.colorbar(sm, orientation='horizontal',label='Asset Wealth',cax=cbaxes)


plt.show()
```



Plot Predictions

[53]:
```
fig, axes = plt.subplots(1, 5, sharey=True,constrained_layout=True, figsize=(12,9))


from matplotlib import colors

divnorm=colors.TwoSlopeNorm(vmin=-4, vcenter=0, vmax=4)
markersize=5
subplot_title_size = 16

axes[0].set_aspect('equal')
plt.suptitle('Asset Wealth Verteilung der besten Modelle fÃ¼r Mosambik', fontsize=26, y=.
↪8, x=0.53)

moz.plot(ax=axes[0], color='white', edgecolor='grey')
rural_2016_df.sort_values(by='Prediction').plot(ax = axes[0], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)

urban_2016_df.sort_values(by='Prediction').plot(ax = axes[0], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)


axes[0].set_xlabel('Latitude', fontsize=13)
axes[0].set_ylabel('Longitude', fontsize=13)
axes[0].set_title('Mosambik 2016', fontsize=subplot_title_size)
axes[0].set_aspect('equal')

moz.plot(ax=axes[1], color='white', edgecolor='grey')
rural_2017_df.sort_values(by='Prediction').plot(ax = axes[1], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)
urban_2017_df.sort_values(by='Prediction').plot(ax = axes[1], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)


axes[1].set_xlabel('Latitude', fontsize=13)
axes[1].set_title('Mosambik 2017', fontsize=subplot_title_size)

axes[1].set_aspect('equal')

moz.plot(ax=axes[2], color='white', edgecolor='grey')
rural_2019_df.sort_values(by='Prediction').plot(ax = axes[2], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)
urban_2019_df.sort_values(by='Prediction').plot(ax = axes[2], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[2].set_xlabel('Latitude', fontsize=13)
axes[2].set_title('Mosambik 2019', fontsize=subplot_title_size)
axes[2].set_aspect('equal')

moz.plot(ax=axes[3], color='white', edgecolor='grey')
rural_2020_df.sort_values(by='Prediction').plot(ax = axes[3], column='Prediction',
                 cmap='coolwarm', norm=divnorm, markersize=markersize)
urban_2020_df.sort_values(by='Prediction').plot(ax = axes[3], column='Prediction',
```
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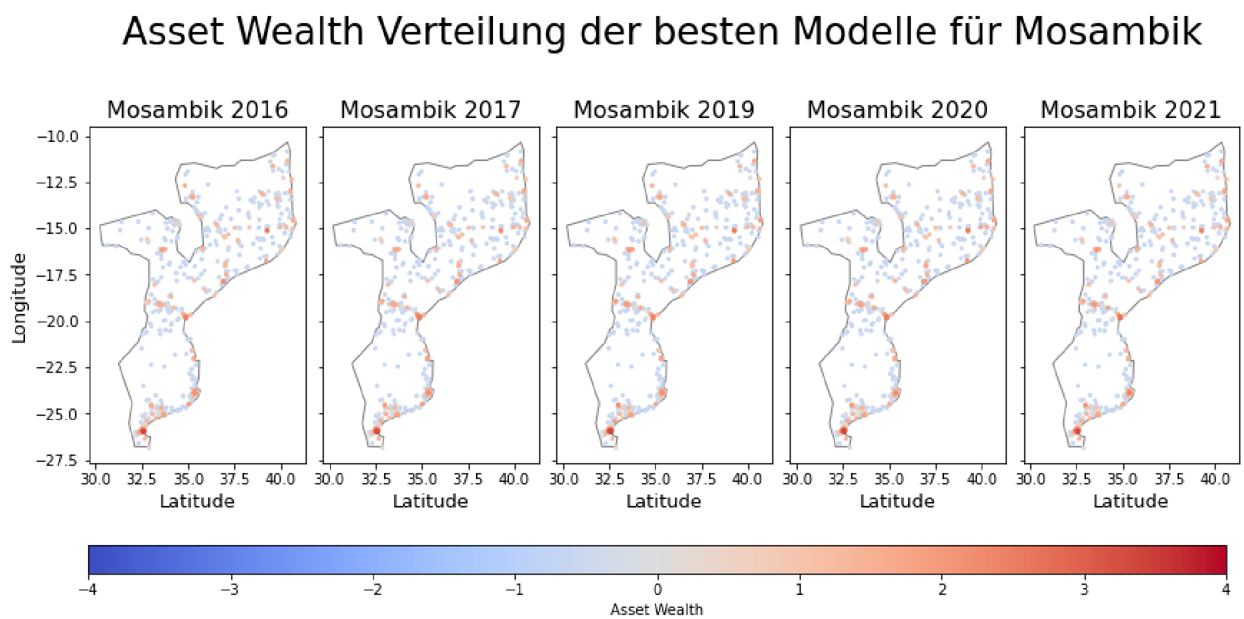
```
                    cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[3].set_xlabel('Latitude', fontsize=13)
axes[3].set_title('Mosambik 2020', fontsize=subplot_title_size)
axes[3].set_aspect('equal')

moz.plot(ax=axes[4], color='white', edgecolor='grey')
rural_2021_df.sort_values(by='Prediction').plot(ax = axes[4], column='Prediction',
                    cmap='coolwarm', norm=divnorm, markersize=markersize)
urban_2021_df.sort_values(by='Prediction').plot(ax = axes[4], column='Prediction',
                    cmap='coolwarm', norm=divnorm, markersize=markersize)
axes[4].set_xlabel('Latitude', fontsize=13)
axes[4].set_title('Mosambik 2021', fontsize=subplot_title_size)
axes[4].set_aspect('equal')

sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=-4, vmax=4), cmap='coolwarm')
cbaxes = fig.add_axes([0.066, 0.2, .92, 0.03])
cbar = fig.colorbar(sm, orientation='horizontal',label='Asset Wealth',cax=cbaxes)


plt.show()
```




```
[54]: data = {'urban': {'2016': urban_2016_df,
                   '2017': urban_2017_df,
                   '2019': urban_2019_df,
                   '2020': urban_2020_df,
                   '2021': urban_2021_df},

        'rural': {'2016': rural_2016_df,
                   '2017': rural_2017_df,
                   '2019': rural_2019_df,
                   '2020': rural_2020_df,
                   '2021': rural_2021_df}
```

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```
        }
statistics = []
for ur, ur_data in data.items():
    for year, pred in ur_data.items():
        statistics.append([ur,
                           year,
                           round(pred.Prediction.min(),2),
                           round(pred.Prediction.max(),2),
                           round(pred.Prediction.mean(),2),
                           round(pred.Prediction.median(),2),
                           round(pred.Prediction.var(),2),
                           round(pred.Prediction.skew(),2),
                           round(pred.Prediction.kurtosis(),2)])
pred_statistics_df = pd.DataFrame(data=statistics, columns=['Urban/Rural','Jahr','Min',
↪'Max', 'Arithmetisches\nMittel','Median','Varianz','Schiefe','Kurtosis'])
pred_statistics_df
```

```
['urban', '2016', 0.32, 3.38, 1.53, 1.45, 0.32, 0.57, 0.7]
['urban', '2017', 0.32, 3.3, 1.55, 1.51, 0.32, 0.47, 0.48]
['urban', '2019', 0.33, 3.36, 1.57, 1.52, 0.3, 0.61, 0.88]
['urban', '2020', 0.35, 3.4, 1.59, 1.53, 0.34, 0.58, 0.55]
['urban', '2021', 0.33, 3.32, 1.57, 1.53, 0.34, 0.53, 0.47]
['rural', '2016', -0.62, 1.02, -0.52, -0.59, 0.04, 4.61, 25.61]
['rural', '2017', -0.63, 1.02, -0.51, -0.59, 0.05, 4.16, 20.34]
['rural', '2019', -0.62, 1.05, -0.51, -0.59, 0.05, 4.47, 23.02]
['rural', '2020', -0.67, 0.96, -0.51, -0.59, 0.05, 4.23, 20.31]
['rural', '2021', -0.59, 0.81, -0.5, -0.59, 0.05, 3.66, 14.73]
```

[54]:

```
  Urban/Rural  Jahr   Min   Max  Arithmetisches\nMittel  Median  Varianz  \
0       urban  2016  0.32  3.38                    1.53    1.45     0.32
1       urban  2017  0.32  3.30                    1.55    1.51     0.32
2       urban  2019  0.33  3.36                    1.57    1.52     0.30
3       urban  2020  0.35  3.40                    1.59    1.53     0.34
4       urban  2021  0.33  3.32                    1.57    1.53     0.34
5       rural  2016 -0.62  1.02                   -0.52   -0.59     0.04
6       rural  2017 -0.63  1.02                   -0.51   -0.59     0.05
7       rural  2019 -0.62  1.05                   -0.51   -0.59     0.05
8       rural  2020 -0.67  0.96                   -0.51   -0.59     0.05
9       rural  2021 -0.59  0.81                   -0.50   -0.59     0.05

   Schiefe   Kurtosis
0     0.57   0.700000
1     0.47   0.480000
2     0.61   0.880000
3     0.58   0.550000
4     0.53   0.470000
5     4.61  25.610001
6     4.16  20.340000
7     4.47  23.020000
8     4.23  20.309999
9     3.66  14.730000
```

4.2.3 Split and copy raw GeoTIFFs to separate directories for preprocessing

[1]:
```
import os
import sys

sys.path.append("..")

from shutil import copyfile

from src.config import csv_path
from src.config import download_path_s2
from src.config import download_path_viirs
from src.config import countries

from src.data_utils import combine_wealth_dfs
from src.data_utils import get_label_for_img


sentinel_prep_path = '/mnt/datadisk/data/Sentinel2/preprocessed/asset/'
viirs_prep_path = '/mnt/datadisk/data/VIIRS/preprocessed/asset/'
```

Sentinel-2

Separate Urban and Rural Files

[3]:
```
urban_files = []
rural_files = []
```

[4]:
```
dir_list = [directory for directory in os.listdir(download_path_s2) if os.path.isdir(os.
↪path.join(download_path_s2,directory)) and any(country in directory for country in␣
↪countries)]

for directory in dir_list:
    urban_files.extend([os.path.join(directory,file) for file in os.listdir(os.path.
↪join(download_path_s2,directory))
                        if file.endswith("u_2.0.tif")])
    rural_files.extend([os.path.join(directory, file) for file in os.listdir(os.path.
↪join(download_path_s2,directory))
                        if file.endswith("r_10.0.tif")])
```

Copy to preprocessing directory (separated by type of region)

[17]:
```
s2_urban_all_path = os.path.join(sentinel_prep_path, "urban", "all")
s2_rural_all_path = os.path.join(sentinel_prep_path, "rural", "all")
```

[17]:
```
'/mnt/datadisk/data/Sentinel2/preprocessed/asset/rural/all'
```

[ ]:
```
for file in urban_files:
    copyfile(os.path.join(download_path_s2,file), os.path.join(s2_urban_all_path, file))
```

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```
for file in urban_files:
    copyfile(os.path.join(download_path_s2, file), os.path.join(s2_rural_all_path file))
```

Get Images for 2012-2014 and 2016-2020

[ ]:
```
wealth_df = combine_wealth(csv_path)
for filename in os.listdir(s2_urban_all_path):
    year = get_label_for_img(wealth_df, filename).SURVEY_YEAR
    if year < 2015:
        copyfile(os.path.join(s2_urban_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2012_2014',filename))
    elif year > 2015:
        copyfile(os.path.join(s2_rural_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2016_2020',filename))

for filename in os.listdir(s2_rural_all_path):
    year = get_label_for_img(wealth_df, filename).SURVEY_YEAR
    if year < 2015:
        copyfile(os.path.join(s2_rural_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2012_2014',filename))
    elif year > 2015:
        copyfile(os.path.join(s2_rural_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2016_2020',filename))
```

VIIRS

Separate Urban and Rural Files

[19]:
```
urban_files = []
rural_files = []
```

[20]:
```
dir_list = [directory for directory in os.listdir(download_path_viirs) if os.path.
↪isdir(os.path.join(download_path_viirs,directory)) and any(country in directory for␣
↪country in countries)]

for directory in dir_list:
    urban_files.extend([os.path.join(directory,file) for file in os.listdir(os.path.
↪join(download_path_viirs,directory))
                        if file.endswith("u_2.0.tif")])
    rural_files.extend([os.path.join(directory, file) for file in os.listdir(os.path.
↪join(download_path_viirs,directory))
                        if file.endswith("r_10.0.tif")])
```

Copy to preprocessing directory (separated by type of region)

[22]:
```
viirs_urban_all_path = os.path.join(viirs_prep_path, "urban", "all")
viirs_rural_all_path = os.path.join(viirs_prep_path, "rural", "all")
```

[ ]:
```
for file in urban_files:
    copyfile(os.path.join(download_path_viirs,file), os.path.join(viirs_urban_all_path,␣
↪file))
for file in urban_files:
    copyfile(os.path.join(download_path_viirs, file), os.path.join(viirs_rural_all_path␣
↪file))
```

Get Images for 2012-2014 and 2016-2020

[ ]:
```
for filename in os.listdir(viirs_urban_all_path):
    year = get_label_for_img(wealth_df, filename).SURVEY_YEAR
    if year < 2015:
        copyfile(os.path.join(viirs_urban_all_path, filename), os.path.join(viirs_urban_
↪all_path[:-3],'2012_2014',filename))
    elif year > 2015:
        copyfile(os.path.join(viirs_urban_all_path, filename), os.path.join(viirs_urban_
↪all_path[:-3],'2016_2020',filename))

for filename in os.listdir(s2_rural_all_path):
    year = get_label_for_img(wealth_df, filename).SURVEY_YEAR
    if year < 2015:
        copyfile(os.path.join(s2_rural_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2012_2014',filename))
    elif year > 2015:
        copyfile(os.path.join(s2_rural_all_path, filename), os.path.join(s2_rural_all_
↪path[:-3],'2016_2020',filename))
```

PYTHON MODULE INDEX

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