2021

Internship Report
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EMJMD COPERNICUS MASTERS IN DIGITAL EARTH, UNIVERSITY OF SALZBURG, AUSTRIA

TERRANEA, MUNICH

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Contents

Summary

As part of EMJMD Masters in Digital Earth the mandatory internship was performed at **Terranea, Munich** from April to July 2021 as a part-time activity. Terranea is a geospatial organization where they aim at creating innovative location-based applications supporting businesses and governments in fulfilling their daily duties. I was tasked with doing remote sensing based tasks the details of which are given below.

Task 1: Tree species classification

The aim of this project was to prepare training data for input to a machine learning model used for tree species classification. The tree species data was collected in point form and they were labeled using satellite image visualization and support the visual interpretation with phenological information visualizing NDVI profiles for the reference year. NDVI time series was the most important signature for classifying trees as different species exhibit different NDVI profiles over the time.

Table 1 Class codes for tree speicies and land cover classes

Class name	Class code
Sealed	1
Woody – needle leaved trees	2
Woody – Broadleaved deciduous trees	3
Woody – Broadleaved evergreen trees	4
Low-growing woody plants (bushes, shrubs)	5
Permanent herbaceous	6
Periodically herbaceous	7
Lichens and mosses	8
Non- and sparsely-vegetated	9
Water	10
Snow and ice	11

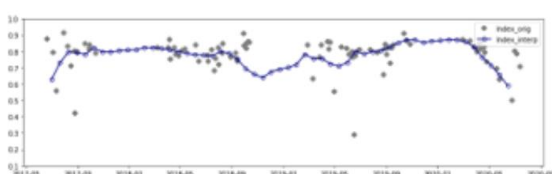


Figure 1 Woody broadleaved trees NDVI

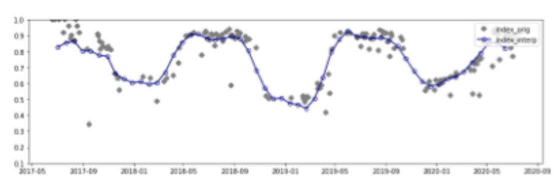


Figure 2 Woody Needle leaved trees NDVI

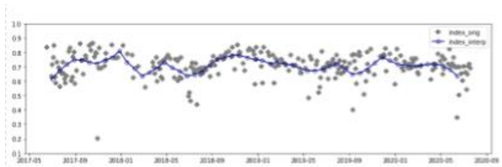


Figure 3 Broadleaved Evergreen

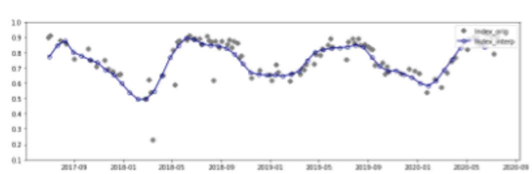


Figure 4 Trees Low growing Woody Plants

Task 2: QGIS Action to visualize NDVI profiles

NDVI profiles were saved in hdf file and Jupyter notebook was used to visualize them. Id of the point was entered and it prints the NDVI profile as this was a time taking task since points were being visualized in QGIS, to tackle this problem and make the task more efficient a custom QGIS action was made using Python. This actions opens the NDVI profile just by clicking at the point in QGIS Canvas. Actions are available as a custom Utility in QGIS and can be created and used as a tool.

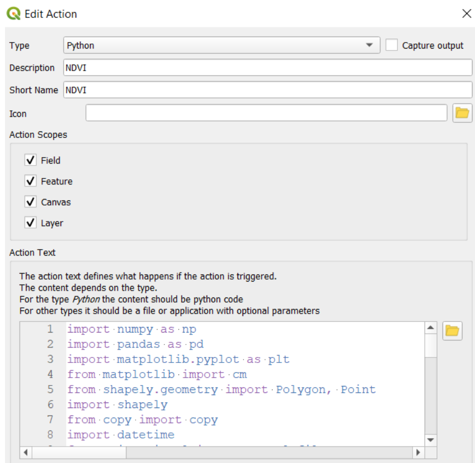


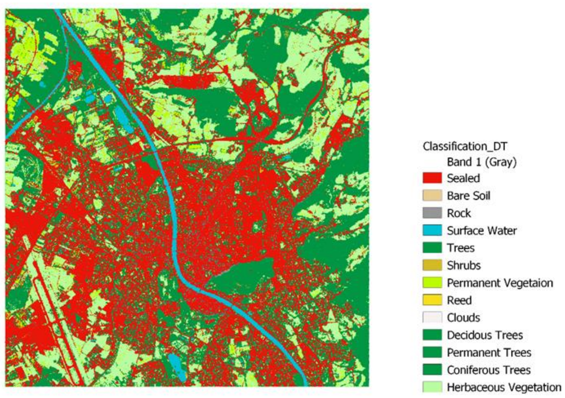
Figure 5 Create QGIS Action

Figure 6 NDVI Profile of the point displayed on canvas

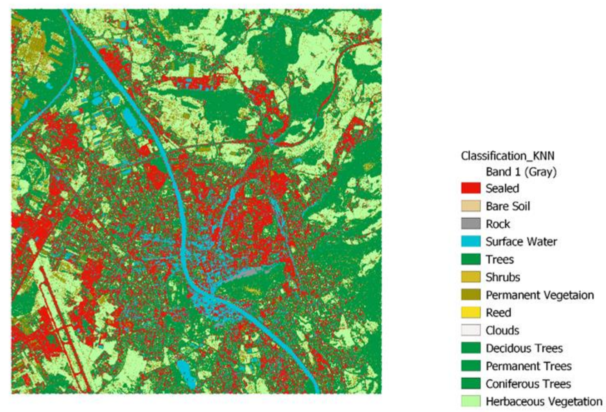
Task 3 Land Cover classification

Machine learning algorithm based land cover classification was performed in SAGA GIS and results and accuracy were different algorithms were compared. Sentinel-2A data was used for LCC and land cover map from Land Use and Land cover survey, Austria was used as a reference map.

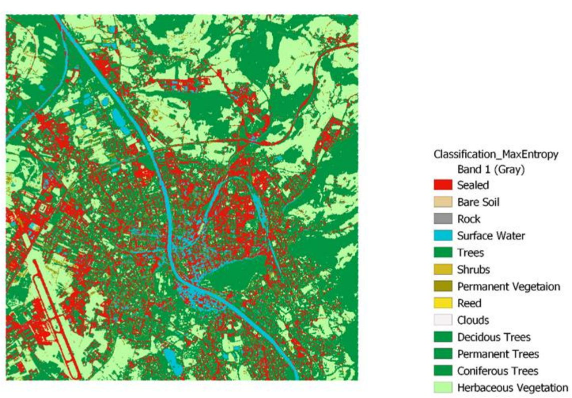
Decision Tree Classification



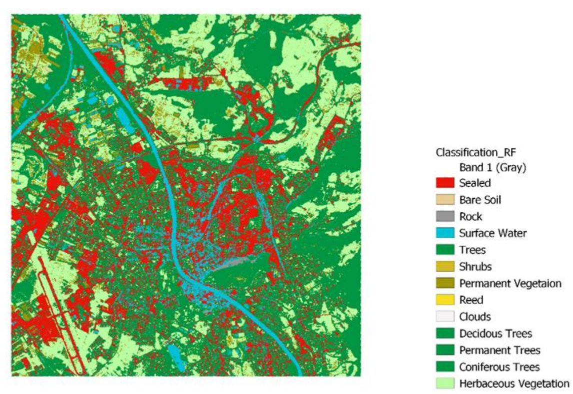
KNN Classification



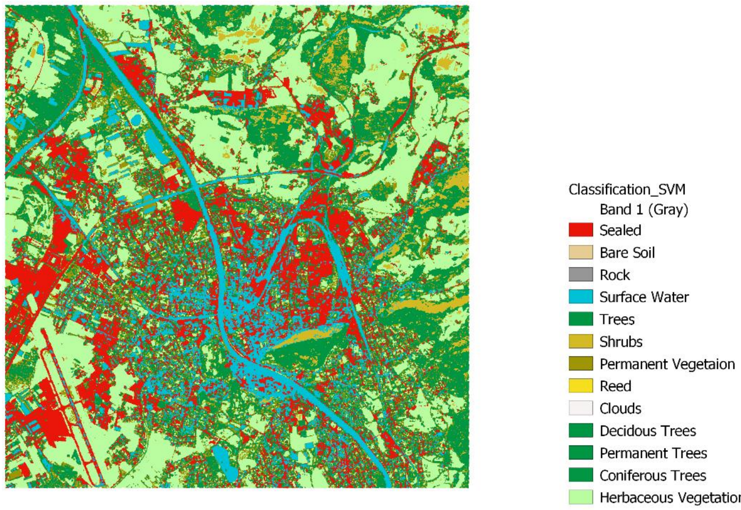
Max Entropy Classification



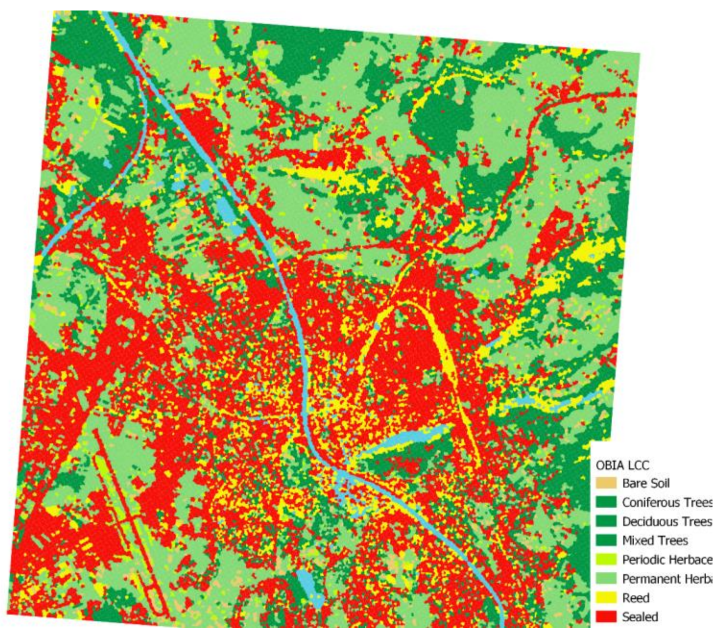
Random Forest Classification



Support Vector Machine Classification



Object based image classification (Maximum Likelihood)



Accuracy Comparison

	DT	RF	Max Entropy	SVM	KNN	OBIA
Overall Accuracy	0.4	0.33	0.32	0.35	0.29	0.68
Kappa's Coefficient	0.16	0.23	0.16	0.28	0.16	0.57

Task 4: Urban Heat Vulnerability Index

The objective of this study is to find the urban heat vulnerability map for the city of cologne, Germany using Landsat 8. Vulnerability depends on exposure, sensitivity and adaptive capacity. This is done by quantitatively evaluating heat vulnerability with the help of its three components as follows:

Weighting of Indices: The indices for exposure, sensitivity and adaptive capacity had equal weight with respect to each other for the calculation of the urban heat vulnerability index.

Exposure: The exposure for the city was obtained by mapping the various hotspots within its urban areas.

Sensitivity: The sensitivity to extreme heat of a city is obtained by identifying the most vulnerable population to these effects of climate change. Whereas extreme heat affects independently the entire urban area, some age groups will be more impacted by it and will suffer from it in terms of health and well-being.

Adaptive Capacity: The adaptive capacity consists of the level of heat resilient infrastructure which is available within the city to protect its citizens against the adverse impacts of extreme heat events. The level of greenery and water-bodies present in the city are well known for reducing these impacts.

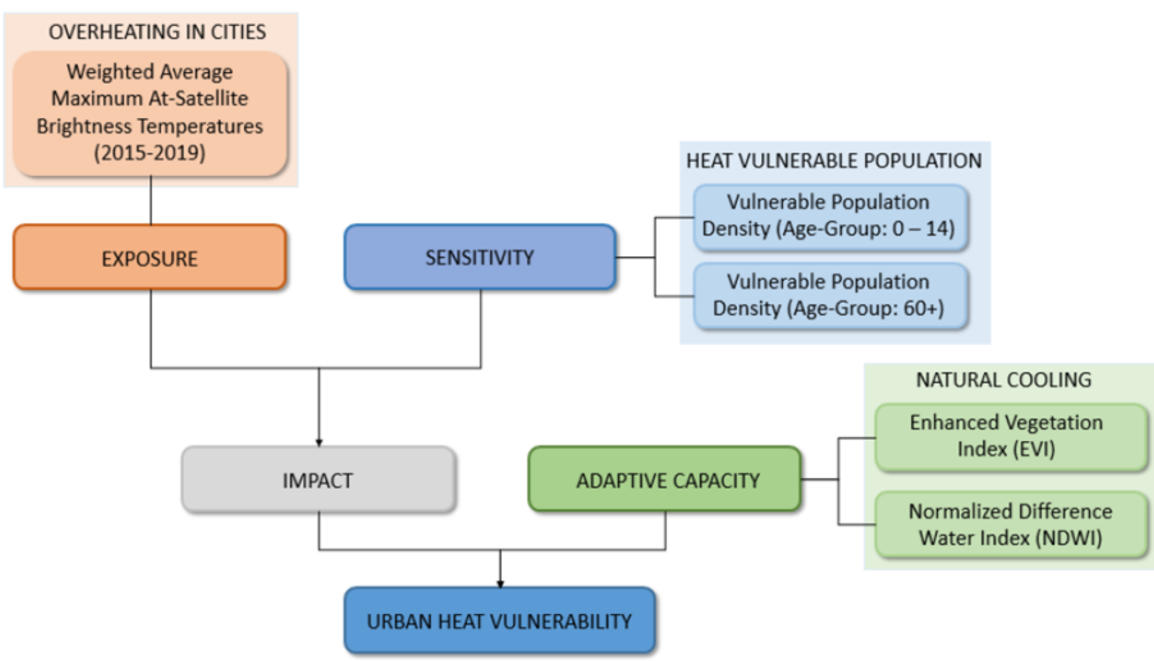
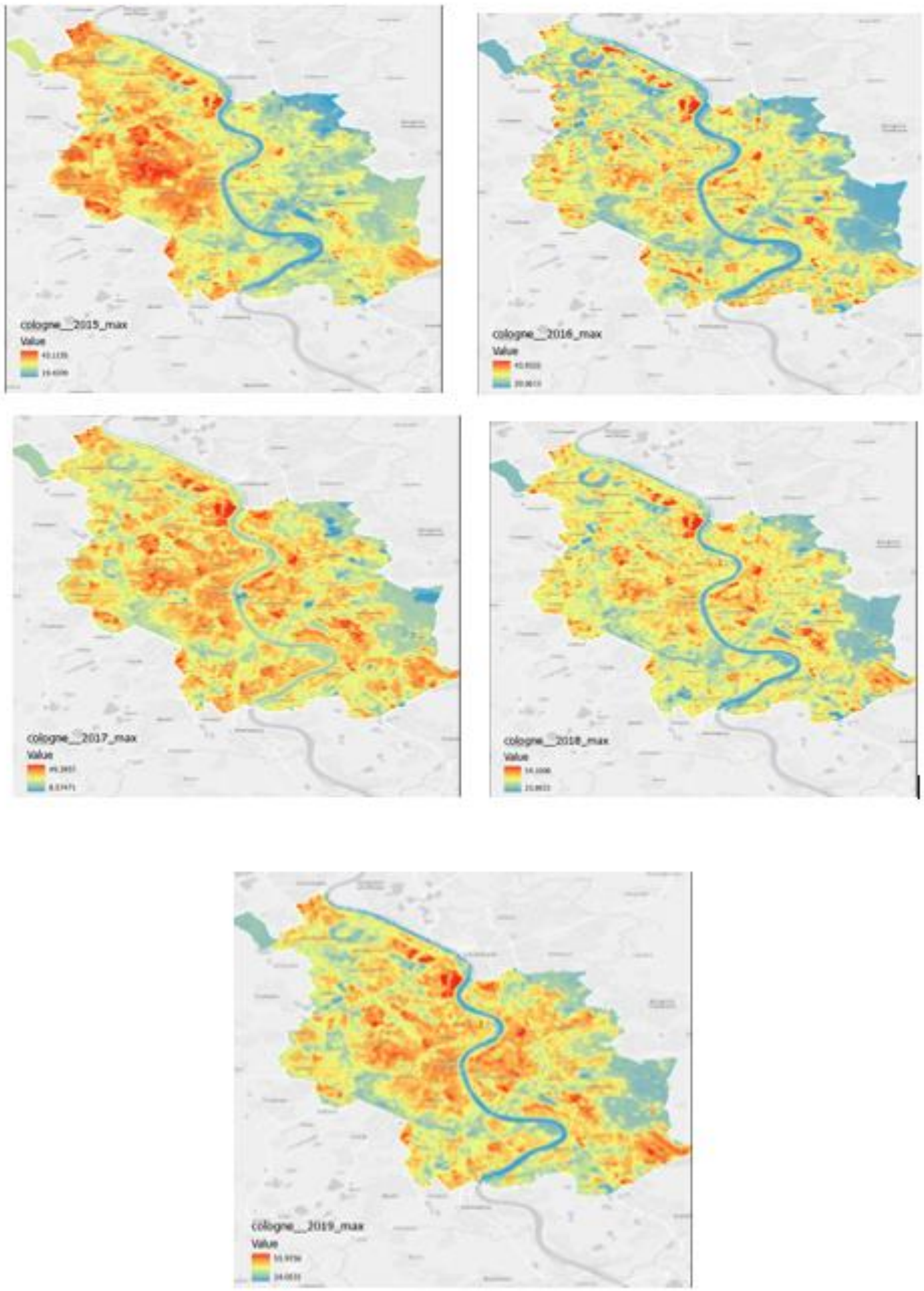


Figure 7 Framework for Heat Vulnerability index calculation

Max Annual Temperature from 2015 to 2019 Cologne



• Weighted Average of Annual Maximum ASB Temperatures

The weighted average of the 5 years was calculated by taking the number of hot days as the weighting factor using the equation given below:

$$T_{avg} = \frac{(T_{max} \times D_{heat})_{2015} + (T_{max} \times D_{heat})_{2016} + (T_{max} \times D_{heat})_{2017} + (T_{max} \times D_{heat})_{2018} + (T_{max} \times D_{heat})_{2019}}{(D_{heat})_{2015} + (D_{heat})_{2016} + (D_{heat})_{2017} + (D_{heat})_{2018} + (D_{heat})_{2019}}$$

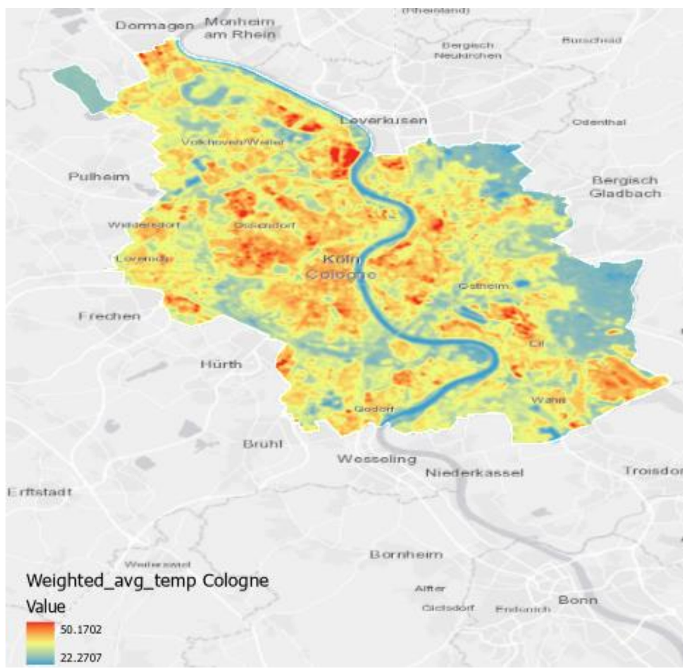
Where,

Tmax : Maximum temperature dataset from Landsat 8 for each year·

Dheat : Number of heat days for each year·

Tavg : Average weighted temperature dataset for all 5 years (2015-2019)

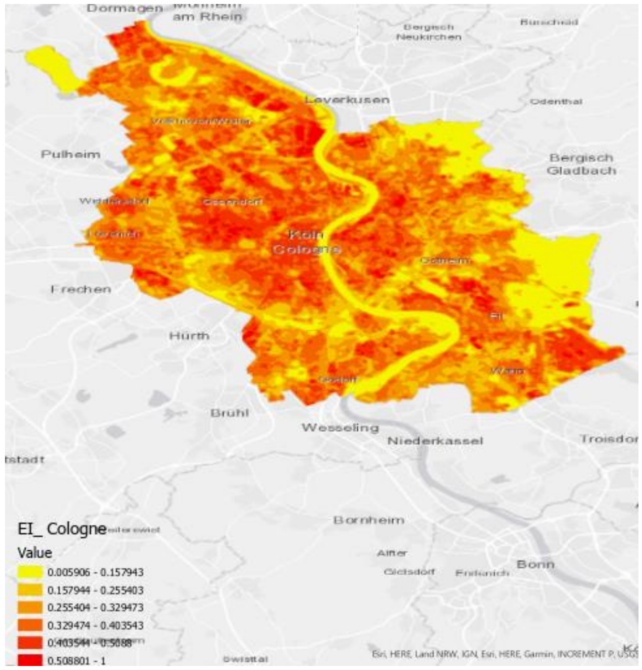
Weighted Average Temperature for Cologne



• Exposure Index (EI)

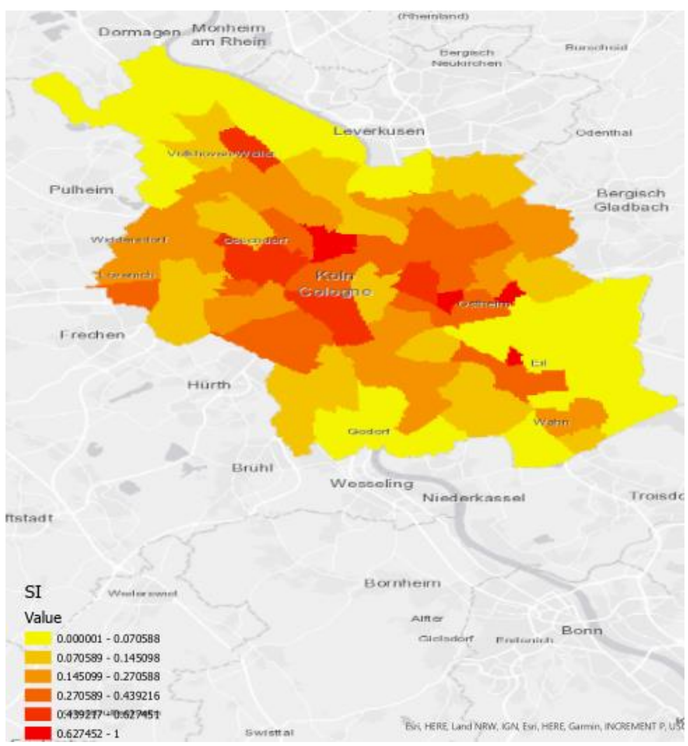
To measure the EI, annual weight average temperatures obtained above were normalized between 32 to 46 degrees Celsius for Karachi and between 22 to 50 degrees Celsius for Cologne to obtain a value between 0 and 1. The following equation was used in Raster Calculator to calculate EI.

Raster –min (raster) / max (raster) - min (raster)



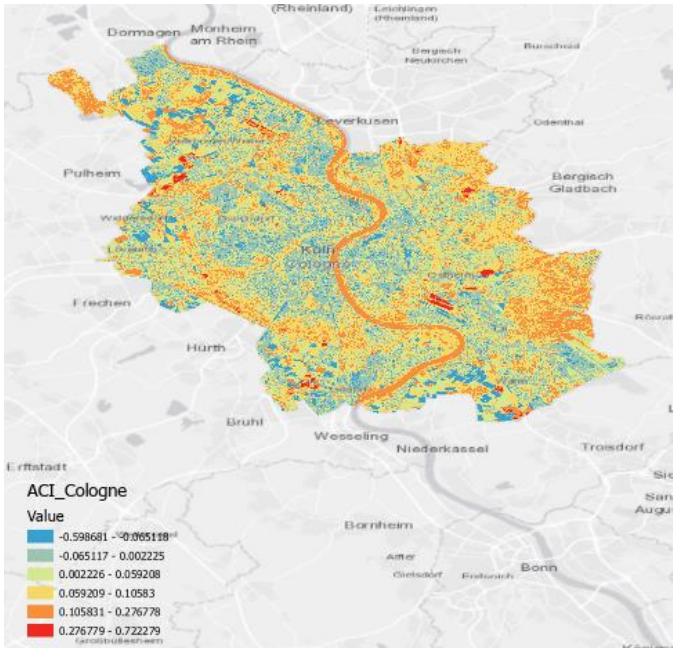
- **Sensitivity Index**

The SI was calculated by adding the vulnerable population densities for Age Groups 1 and 2 and then normalizing it to obtain a value between 0 and 1.



- **Adaptive Capacity Index:**

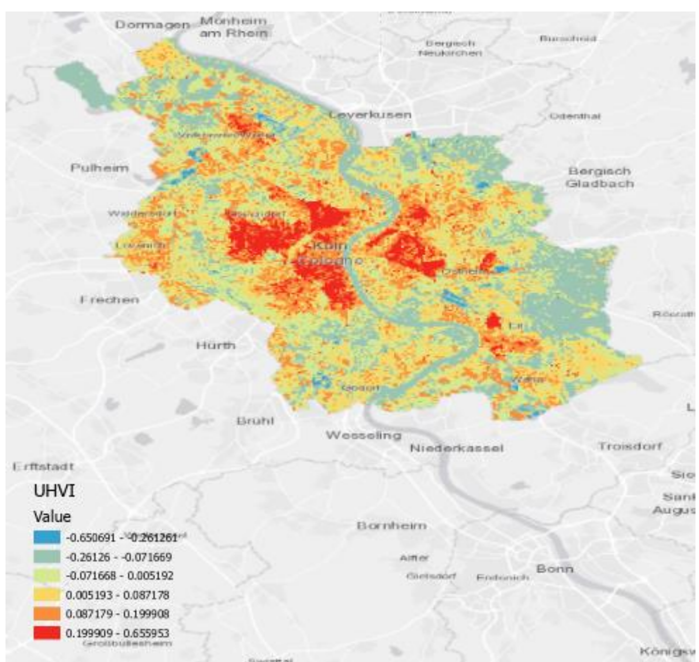
To obtain the ACI, the NDVI and the NDWI were added.



- **Calculation of Urban Heat Vulnerability Index (UHVI)**

UHVI was calculated by obtaining the difference between the ACI and the product of EI and SI as shown below:

$$UHVI = EI * SI - ACI$$



Task 5: Drought Indices Calculation

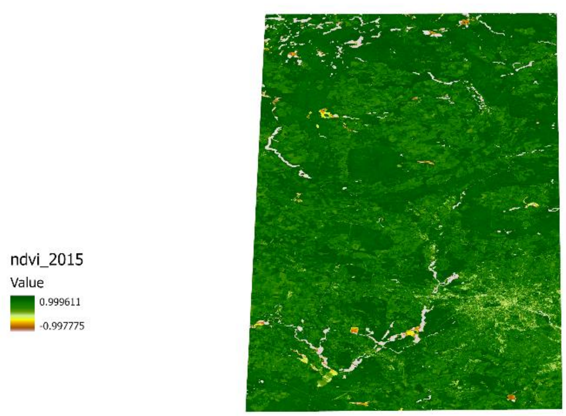
Goal of this task was to calculate, visualize and compare different satellite data based drought indices. Sentinel 2A data was used for drought index calculation, images for April 2015 and 2020 were downloaded. Raster calculator tool was used for drought index calculation. The following two satellite data based indices were calculate for year 2015 and 2020:

- Vegetation condition index
- Global vegetation moisture index

- **Vegetation condition index**

VCI is used to identify drought situations and determine the onset, especially in areas where drought episodes are localized and ill defined. It focuses on the impact of drought on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values. It is used in conjunction with NDVI. It is calculated as follows:

(NDVI_raster - min(NDVI) / max(NDVI) - min(NDVI))*100



- **Global vegetation moisture index**

It is used to estimate vegetation moisture content and is an effective indicator of drought condition. It is calculated as:

$$(NIR+0.1) - (SWIR+0.02) / (NIR+0.1) + (SWIR+0.02)$$

For sentinel 2 formula is as follows:

$$(band9+0.1) - (band12+0.02) / (band9+0.1) + (band12+0.02)$$