Fakultät für Geoinformation

HOCHSCHULE FÜR ANGEWANDTE WISSENSCHAFTEN MÜNCHEN

Bachelorarbeit

Urban dynamics in the greater Phoenix area

Detection of urban areas and their change based on Google Earth Engine and an expert-knowledge based decision-tree

angefertigt von

Samuel Adolph

Studiengang: Geoinformatik und Navigation

Betreuer: Prof. Dr. Michael Schmitt

Die Arbeit wurde angefertigt in Kooperation mit:

Dr. Daniele Cerra und Dr. Stefan Auer

Deutsches Zentrum für Luft- und Raumfahrt (DLR)

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LIST OF ABBREVIATIONS

SAR	Synthetic Aperture Radar
HH	Horizontal-Horizontal
VV	Vertical-Vertical
HV	Horizontal-Vertical
VH	Vertical-Horizontal
NIR	Near-Infrared
SWIR	Short-Wavelength Infrared
NDBI	Normalized Difference Build-up Index
NDVI	Normalized Difference Vegetation Index
NDTI	Normalized Difference Tillage Index
RGB	Red Green Blue
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives

ABSTRACT

Growing urbanization has become a major concern in the combat of climate change. In order to tackle the problems occurring from unsustainable expansion of cities, it is necessary to first quantify the changes in built-up areas. This thesis presents a way of detecting newly built urban areas on the example of Phoenix, Arizona. The Phoenix Metropolitan Area has been the fastest growing region of the United States in the last years. Based on an expert knowledge decision tree, the implemented methodology in this thesis relies only on publicly available data and tools in order to allow anyone to use, recreate and built upon it. The Google Earth Engine platform was used to make two separate classifications of urban change using Sentinel-1 and Sentinel-2 data. The combination of these independent classifications proved to be a good lower bound for the detection of newly built urban areas.

1 INTRODUCTION

The increasing amount of urbanization around the globe together with a growth of population and built-up areas massively impacts the environment (Uttara, 2012). Therefore, urbanization has become a major focus of environmental efforts to a more sustainable future. This is shown by the fact that “Sustainable Cities and Communities” has become a part of the 2030 Agenda for Sustainable Development (Johnston, 2016). Earth observation on a global scale plays an important role in monitoring the development of urban areas. This has also been recognised by the UN as an useful tool to tackle the global problem of climate change and sustainability (United Nations Office for Outer Space Affairs, 2018).

One major barrier to sustainable urban expansion is water scarcity (Hoekstra et al., 2012). This is especially pronounced in dry, desert areas like the Colorado River Basin with cities like Las Vegas, Denver and Phoenix (Wang & Upreti, 2019).

Satellite based remote sensing allows for an independent and time continuous analysis of the whole earth. This is an important factor, as the combination of different, locally made resources is time consuming and also not a reliable source as those studies are regionally biased and sometimes data - even for large cities - is missing (Seto et al., 2011).

In order to enable everyone to use and reproduce the results of this thesis, special care was taken to only use publicly available data and tools. More specifically data from the EU Copernicus programme, namely Sentinel-1 and Sentinel-2 missions was used. As a processing platform for the data Google Earth Engine was used, allowing anyone a powerful cloud-based computation of satellite data.

This thesis is focussed on the detection of newly built-up areas with an approach that can be applied globally. Its straightforward methodology without the reliance on complex machine-learning algorithms, enables for a quick application to different areas.

1.1 SATELLITE IMAGE DATA

The satellite images used in this thesis were provided by the European Space Agency's Copernicus programme. This mission provides different kinds of high-resolution images on a free to use basis (Attema, 2005; Sentinel- & Eop-sm, 2010). For this study data from the missions Sentinel-1 and Sentinel-2 was used.

1.1.1 SENTINEL-1

One important source of data for this study were Synthetic Aperture Radar (SAR) images in the C-Band provided by the Sentinel-1 mission. As buildings have good reflectance in the C-Band radar images this promised to be a valuable data source for our study. The Sentinel-1 images consist of 4 bands. There are two different polarisations emitted, vertical and horizontal. And both of those are also received individually by the sensor. This gives us Horizontal-Horizontal (HH), Vertical-Vertical (VV), Vertical-Horizontal (VH) and Horizonal-Vertical (HV) bands. The images used in this thesis are at a 10-meter resolution and in a logarithmic scale.

Because buildings have large, regular surfaces and can act as corner reflectors they have strong reflectance in the VV and HH bands. The same applies to water surfaces as they are mostly smooth. Other, more irregular surfaces, like vegetation or soil show less reflectance in those bands.

1.1.2 SENTINEL-2

The other source of data used in the study are images from the Sentinel-2 mission. These images have 13 different bands, ranging from 400nm wavelength to 2300nm. In this study the bands shown in Table 1 were used.

Table 1: Sentinel-2 bands

BAND	**B4**	**B8**	**B11**	**B12**
PROPERTY	Red	NIR	SWIR	SWIR
BANDWIDTH	665	833	1613	2202
RESOLUTION	10	20	20	20

For our purposes, three different indices based on these bands were used, which are described in the following paragraphs.

1.1.2.1 Normalized Difference Build-up Index

The Normalized Difference Build-up Index (NDBI) is well suited for the detection of build-up areas based on the surface reflectance of the ground (Zha et al., 2003). The original paper has proposed this in regard to Landsat TM images, but as the band are similar this can be directly transferred to the images taken by the Sentinel-2 satellites. The calculation of the index in this study was done as following:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{1}$$

Where SWIR is the value of band 12 and NIR is corresponding to band 8.

1.1.2.2 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a widely used metric for the detection of land areas with a vegetative cover (Carlson & Ripley, 1997). The index shows positive values for vegetated areas and negative values for other areas like water or build-up areas. It is calculated as followed:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

Where NIR is band 8 and RED is the red band of Sentinel-2, namely band 4.

1.1.2.3 Normalized Difference Tillage Index

The Normalized Difference Tillage Index (NDTI) is mainly used for the detection and mapping of crop residue and other dead vegetation (Hively et al., 2018). In combination with the NDVI, which is only detecting living vegetation, this can be valuable in the detection of non-urban areas. This can also mitigate seasonal effects or misclassification because of droughts (Rouibah & Belabbas, 2020). The calculation of the NDTI was done as follows:

$$NDTI = \frac{SWIR_{11} - SWIR_{12}}{SWIR_{11} + SWIR_{12}} \tag{3}$$

Where $SWIR_{11}$ is Sentinel-2 band 11 and $SWIR_{12}$ is the corresponding band 12.

1.2 Google Earth Engine

Google Earth Engine is an online computing platform providing easy access to satellite imagery and has a built-in analysis tool running on JavaScript (Gorelick et al., 2017). It is free to use for research and educational purposes. Furthermore, it provides an extensive API with a lot of built-in functionality. Everything in this study was done within the Google Earth Engine, as it provides a comprehensive toolset from accessing satellite data to visualizing on a map.

1.3 Study Area

The study area is the greater Phoenix area, located in Arizona, US. This area is in the south-west of the country and has seen a rapid growth of population and thereby built-up land over the last years. The Maricopa county, containing the majority of the Phoenix Metropolitan Area, has seen an increase in population by 17.5% from 3.81 million inhabitants in 2010 to 4.48 million in 2019 (United States Census Bureau, 2019).

As the climate in this area is arid with low annual rainfall, it was optimal for a number of reasons. Not only is it more interesting to look at such areas in detail, as environmental impacts such as water scarcity are more prominent, but it is also easier to evaluate, as less pre-processing of Sentinel-2 data is needed, because of low cloud cover.

2 METHODS

The approach for this study was to develop two different classification models for urban change detection, which complement each other. This was done by using one algorithm which classifies the area into urban and non-urban areas at two different times and then comparing those. This was done with an index-based approach using Sentinel-2 data.

The other method was a direct detection of temporal change using Sentinel-1 data from different times and comparing these. This approach is shown in Figure 1. The source code was made publicly available, see page 26.

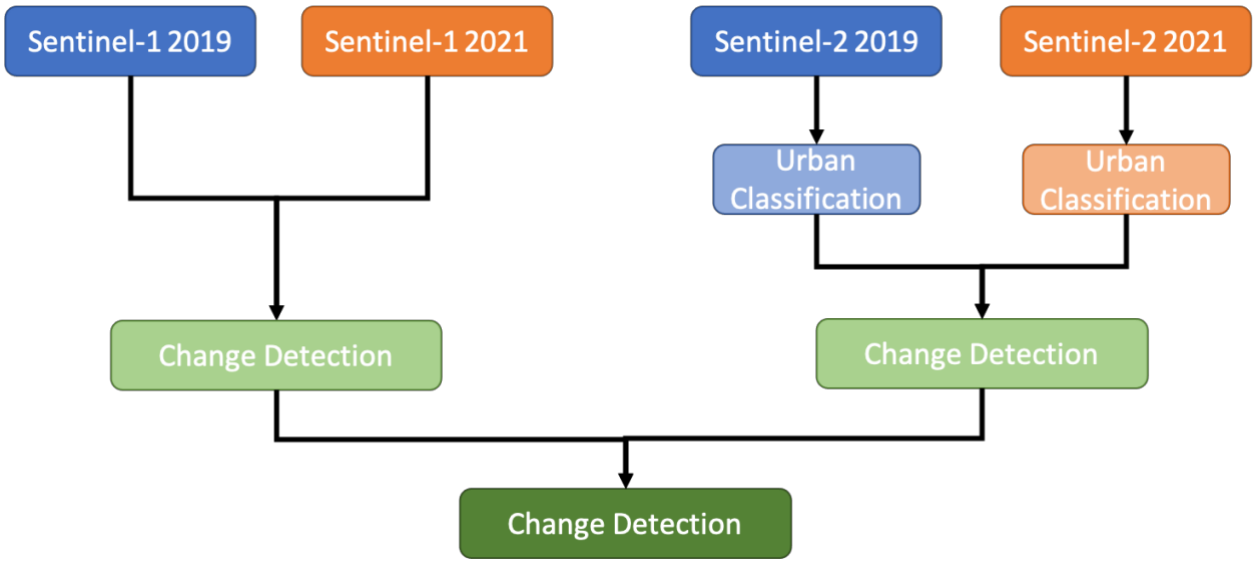

Figure 1: Methodological overview of the classification process

2.1 SENTINEL-1

To first get a good detection of new urban areas, Sentinel-1 data from two different times were used. As buildings have good reflectance in the radar images, we can assume that a strong increase in the pixel intensity for a selected scene can be a result of new buildings.

As the goal was a direct comparison between different images taken by the Sentinel-1 satellites, only images with the same orbit type, in this case *"ascending"*, were considered. In order to mitigate the problem of speckles in the Sentinel-1 images, the mean value of a time series of images was used. As buildings usually take several months to construct, a timespan of 60 days was used for the selection of images. This

resulted in 5 images on average. There was no other preselection done, as cloud cover is not a concern with SAR images.

For the detection of strong changes between the two times, the older image's VV band was subtracted from the newer one. In order to now get a binary classification into areas with change and ones without significant change, a threshold was applied.

2.2 SENTINEL-2

Another approach to detecting newly built urban areas was to first make a classification of the scene into urban and non-urban areas. For this an algorithm was developed based on a decision tree using three main classifying indices, namely NDBI, NDVI and NDTI.

In a first pre-processing step the same 60-day timeseries as with Sentinel-1 was selected. Then all images with a cloudy pixel percentage above 15 percent were excluded. This resulted in 8 images on average. For a reduction in noise and cloudy pixels the median of the remaining images was taken. This process resulted in a cloud-free noise reduced single image.

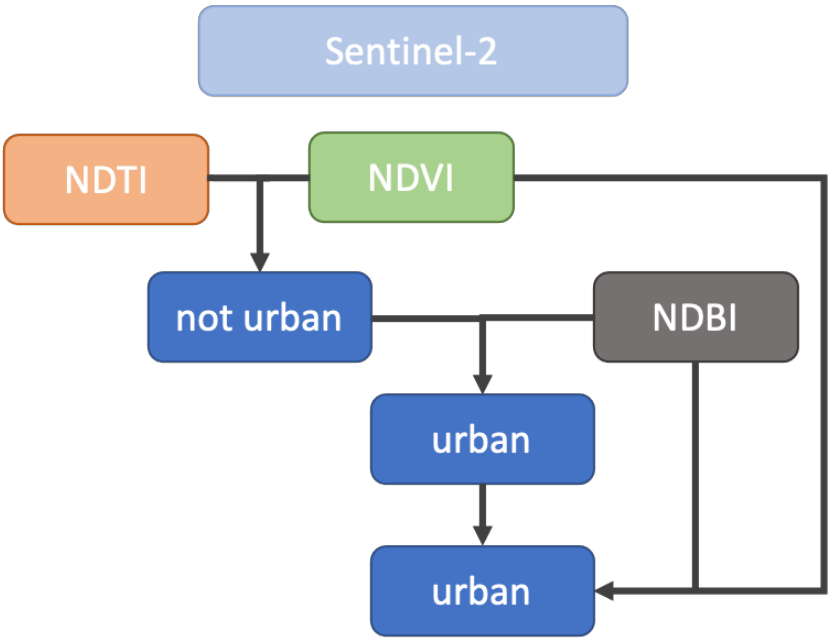

Figure 2: Decision tree of the first step of the classification

Figure 2 shows the general overview over the decision tree used for this classification. In a first step the NDBI was calculated and then a threshold was applied, in order to get a first classification on an urban area. Then the pixels where the NDBI or the NDTI was strong were classified as non-urban. These two classifications were then merged.

As a second step, the threshold of the NDBI was increased and the resulting areas in combination with a low NDVI then considered as urban. This resulted in an intermediate classification.

To further improve the algorithm, a buffer zone around the urban areas was created, where a more relaxed threshold of the NDBI was then applied. This was done by diluting the first intermediate classification with a circular kernel with a size of 40 meters.

In order to detect the changes in the built-up areas this classification was done to two time-separated images. The first step was to dilute the older scene, again with the same kernel as above. Then the final area where change was detected was classified as the area where in the older scene there was no urban area but in the newer scene there was.

2.3 Combination of Sentinel-1 and Sentinel-2

The two very different approaches to the change detection were then combined to eliminate each other's weakness. As the Sentinel-1 approach just detects changes, which don't necessarily mean that there are newly constructed buildings, there is a need to cross reference it. For this, the two methods were applied to the same region and the same timeframes. Then the final classification of the two was combined by dilating the Sentinel-2 classification with a circular kernel having a width of 80 meters and then overlapping with the classification from Sentinel-1. As the Sentinel-2 classification has a pixel size of 20 meters, the final classification also had the same resolution.

2.4 Evaluation Metrics

As a ground truth a selected area was manually classified, using Sentinel-2 RGB images. Polygons were created where in the older image, there was no building, but in the newer image there was. From these polygons a binary image with the same pixel size as the classification from Sentinel-1 and Sentinel-2 was created in order to make a comparison.

For the change detection of built-up areas, the performance of the individual classifications, as well as the combined classification, is evaluated by the overall accuracy, the precision, recall and F1 score, which are defined as follows:

$$overall\ accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

$$precision = \frac{TP}{TP + FP} \tag{5}$$

$$recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1\ score = \frac{2 * precision * recall}{precision + recall} \tag{7}$$

where TP (true positives) is the number of pixels where the ground truth and the classifier show a detected change, TN (true negatives) are considered as such, when both show the pixels as no detected change. FP (false positives) are the pixels, where the classifier shows a detection of change, but there is none in the ground truth, and FN (false negatives) are pixels where there was change, but not detected by the classification.

3 RESULTS

The timeframe used contained the first 60 days of 2019 and the first 60 days of 2021. In order to mitigate seasonal effects, like plant growth, a selection of similar seasons was necessary. This selected area, suburbs in the north-west of Phoenix just along a major highway, is shown in Figure 3.

Figure 3: Sentinel-2 RGB median image from 2019 (left) and 2021 (right)

3.1 Change Detection with Sentinel-1

The Sentinel-1 approach described in section 2.1 was then used on this selected area, in order to detect the occurring changes in high-reflectance objects. As a threshold for the classification of significant changes a value of 5.0 was used. The detected changes can be seen in Figure 4.

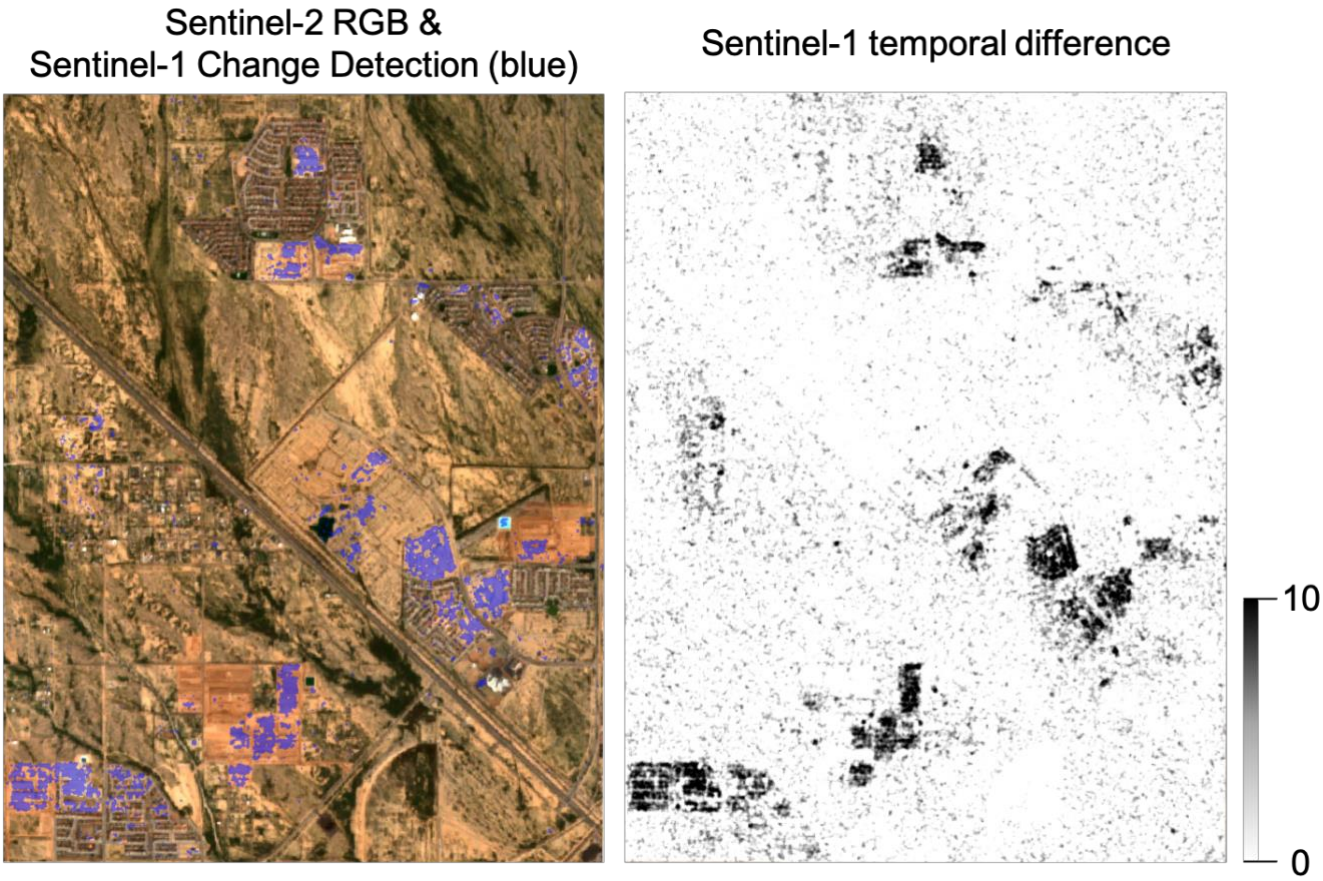

Figure 4: Sentinel-2 RGB (2019) with detected changes using Sentinel-1 data shown in blue (left). The difference between the older and newer Sentinel-1 image (right).

3.2 Urban Classification and Change Detection based on Sentinel-2

The Sentinel-2 method described in section 2.2 was then applied to the same region. The intermediate step, the detection of build-up areas is shown in Figure 5.

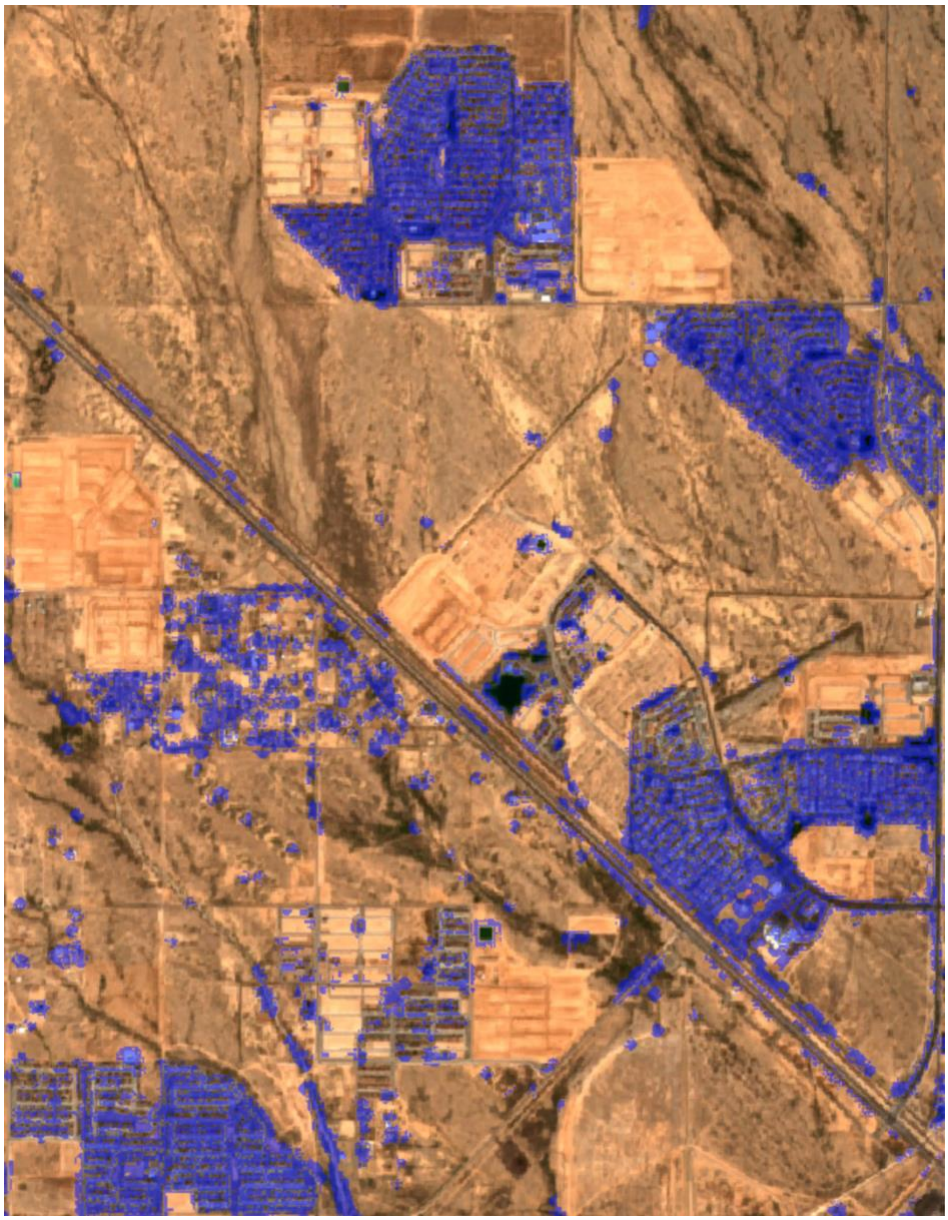

Figure 5: Sentinel-2 RGB (2021) with detection of built-up areas shown in blue

From there the final change detection was calculated using the method described in section 2.2. The resulting classification is shown in Figure 6.

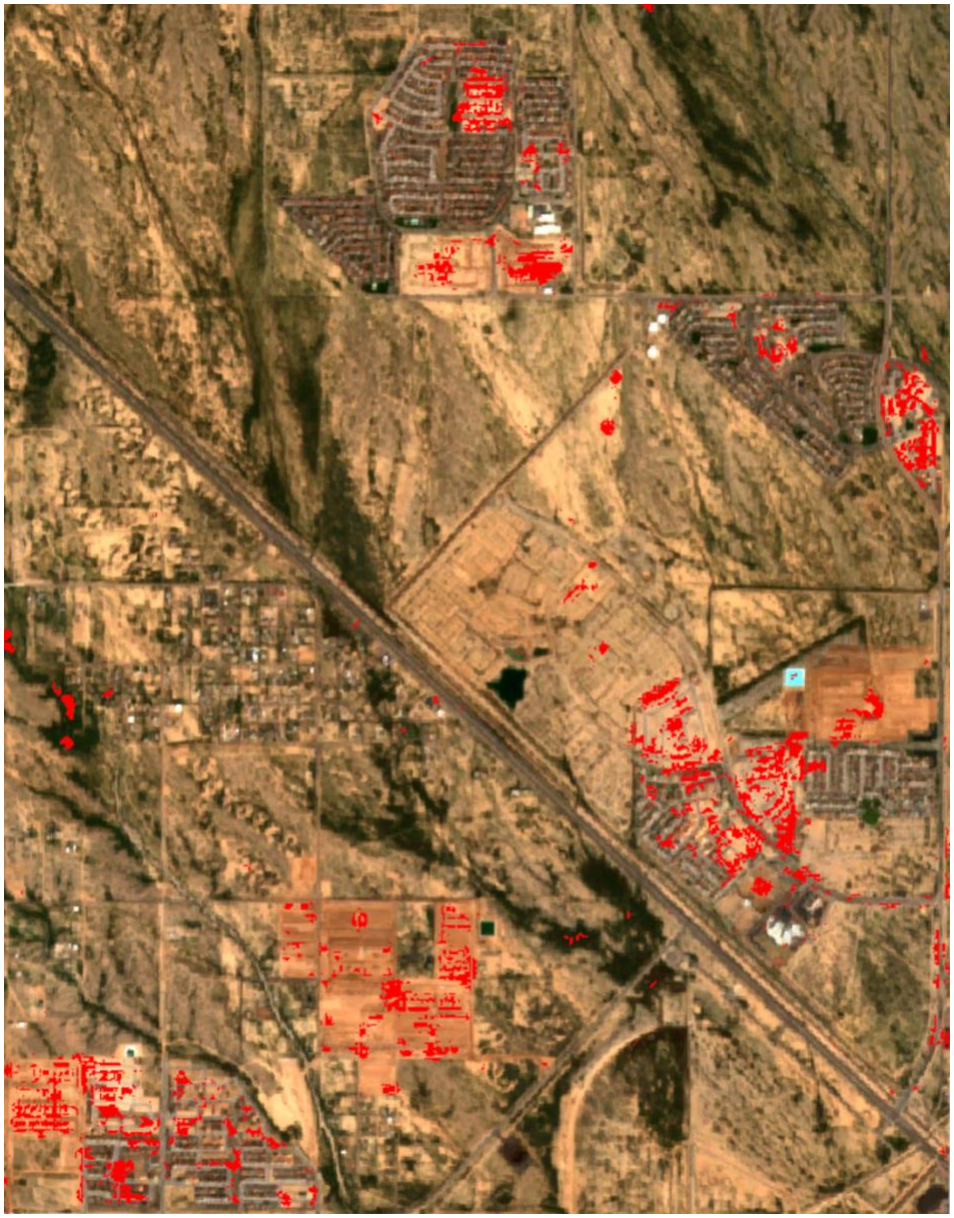

Figure 6: Sentinel-2 RGB (2019) with detected changes using Sentinel-2 data shown in red

3.3 Combination of Sentinel-1 and Sentinel-2

The two different classifications using Sentinel-1 and Sentinel-2 from section 3.1 and 3.2 were then combined into a final classification with the method described in 2.3. The resulting final classification can be seen in Figure 7.

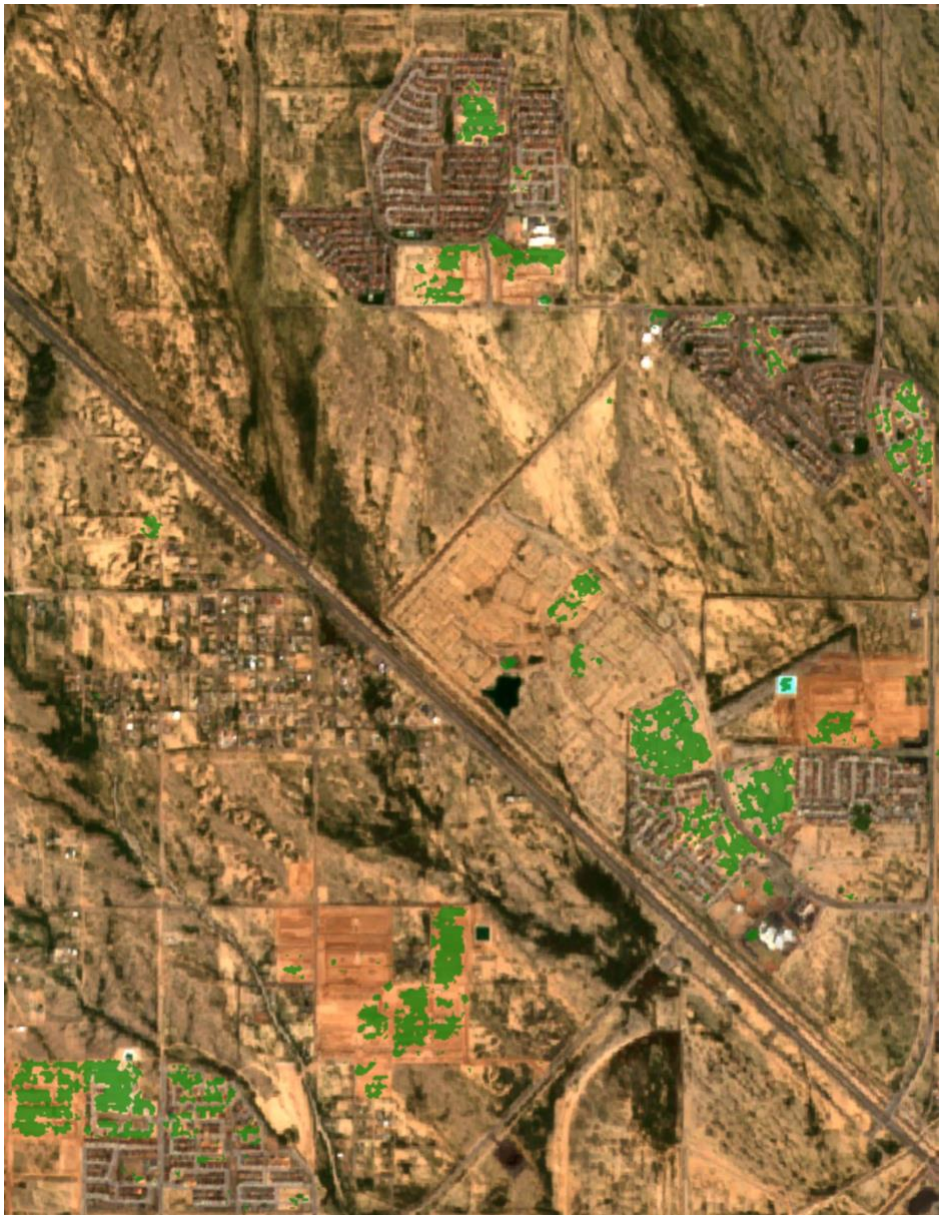

Figure 7: Sentinel-2 RGB (2019) with detected changes using Sentinel-2 and Sentinel-1 data shown in green

The same classification has also been applied to another area in the south-east of Phoenix in order to test in a slightly different setting, with a lot of already existing urban areas and also some agriculture, this is shown in Figure 8.

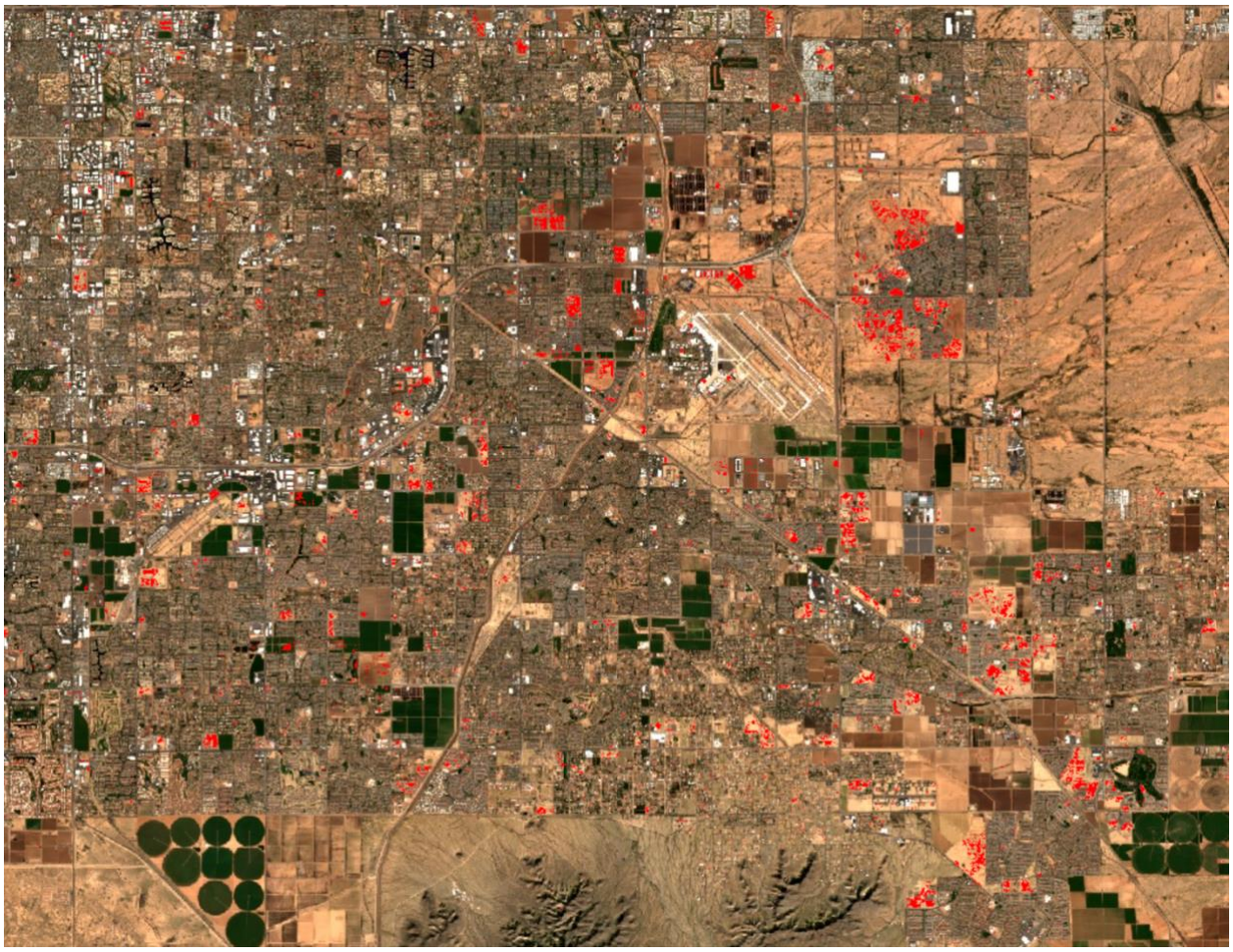

Figure 8: Sentinel-2 RGB (2019) of south-eastern Phoenix with detected changes, using Sentinel-1&2 shown in red.

3.4 VALIDATION

The validation was done based on a ground truth shown in Figure 9. The green polygons are areas where new buildings were constructed in the considered timeframe from 2019 to 2021.

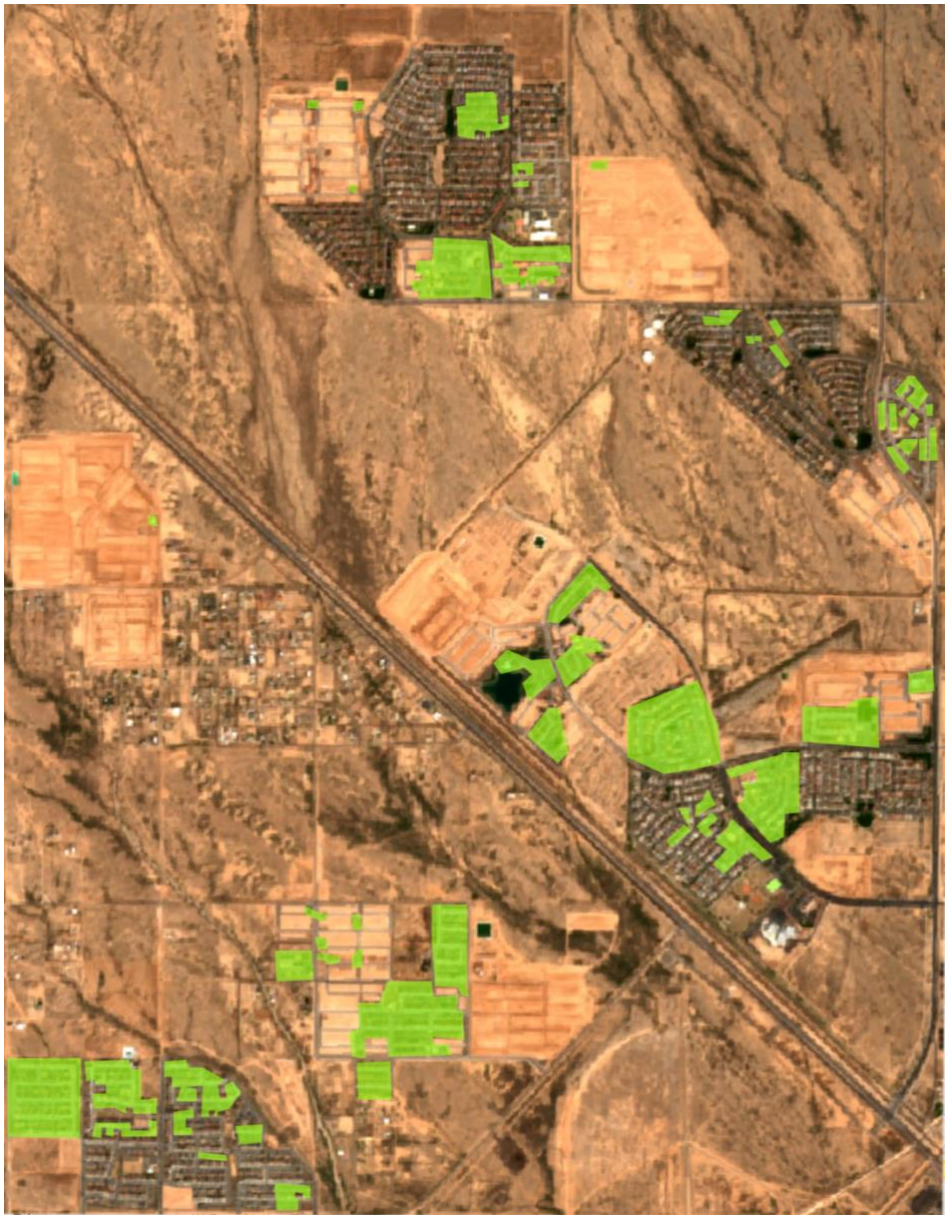

Figure 9: Sentinel-2 RGB (2021) with polygons in green describing the ground truth, where new buildings appeared since 2019

The evaluation metrices described in section 2.4 were then applied to all tree classifications (see Figure 10).

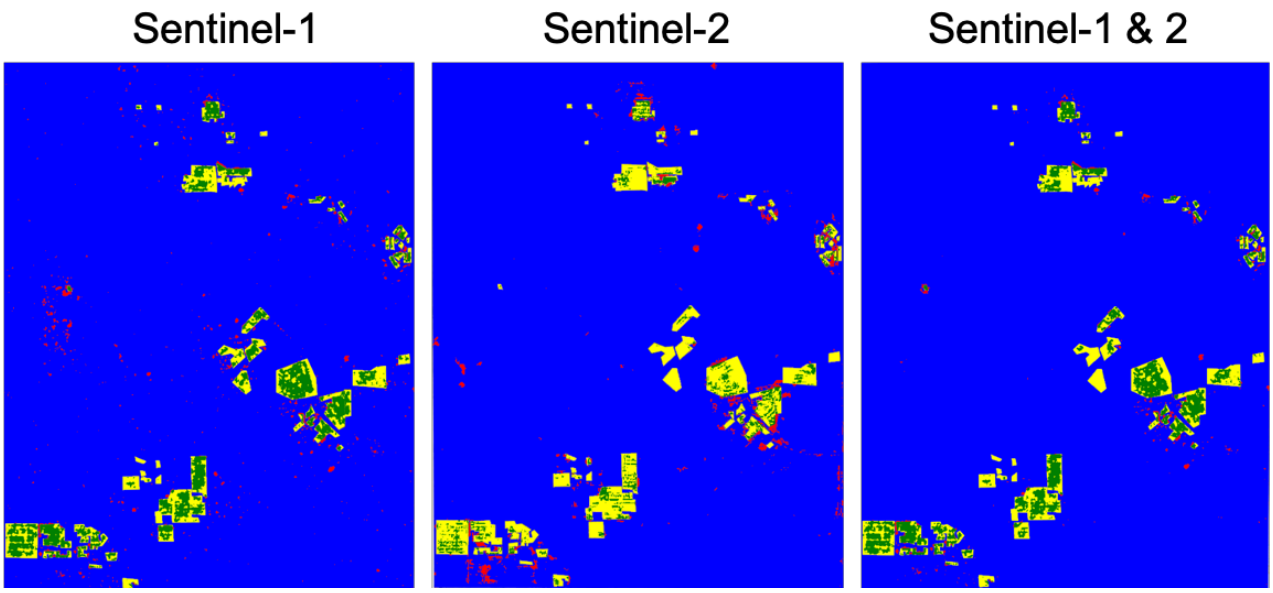

Figure 10: Evaluation of the classifications. Shown in green are true positives, red are false positives, blue are true negatives and yellow are false negatives

From this, the performance scores were calculated by applying the equations (4) - (7). The results can be seen in Table 2.

Table 2: Evaluation metrics for change-detection classification

	Sentinel-1	**Sentinel-2**	**Sentinel-1 & Sentinel 2**
accuracy	0.968	0.944	0.968
precision	0.798	0.402	0.898
recall	0.517	0.183	0.429
F1 score	0.627	0.251	0.580

4 DISCUSSION

The results showed that the change detection of urban areas can be successfully done with the methods developed in this thesis. The overall accuracy for all areas is quite high with around 95% (see Table 2). As only a small portion of our test area has actual change, there is a big imbalance between positives and negatives. Working with such datasets usually requires other metrics, such as precision and recall.

Considering only the Sentinel-1 approach the classification is already quite good. This can be seen by the high F1 score of 0.627. The Sentinel-2 approach seems a bit lacking considering the relatively low precision of 0.402 and recall of 0.183 but can still provide valuable information as seen by the increase in the precision of the combined classification by 12.5% when compared to only using the Sentinel-1 data. This can give a good lower bound for the area of newly constructed urban zones.

The relatively low recall value of all classifications can also be a consequence of an inaccurate ground truth, as polygons were created spanning a whole new block of buildings, whereas the resolution of the Sentinel-1 classification is finer, resulting in a difference in classification. An indication for this is, that all new neighbourhoods in the test area were detected, but not to the full extent of the ground truth. An example for this is shown in Figure 11. This whole new neighbourhood was considered as a newly built-up area in the ground truth as classifying individual buildings was not feasible with the used methods. But in the final classification only roughly 2/3 of the area was detected as a newly built-up area, because mainly the houses were detected but not their backyards. This then results in a lot of false negatives in the evaluation, giving an explanation for a low recall of only 0.429. With a better ground truth for validation purposes, this low recall could improve drastically without changing the classifying algorithm.

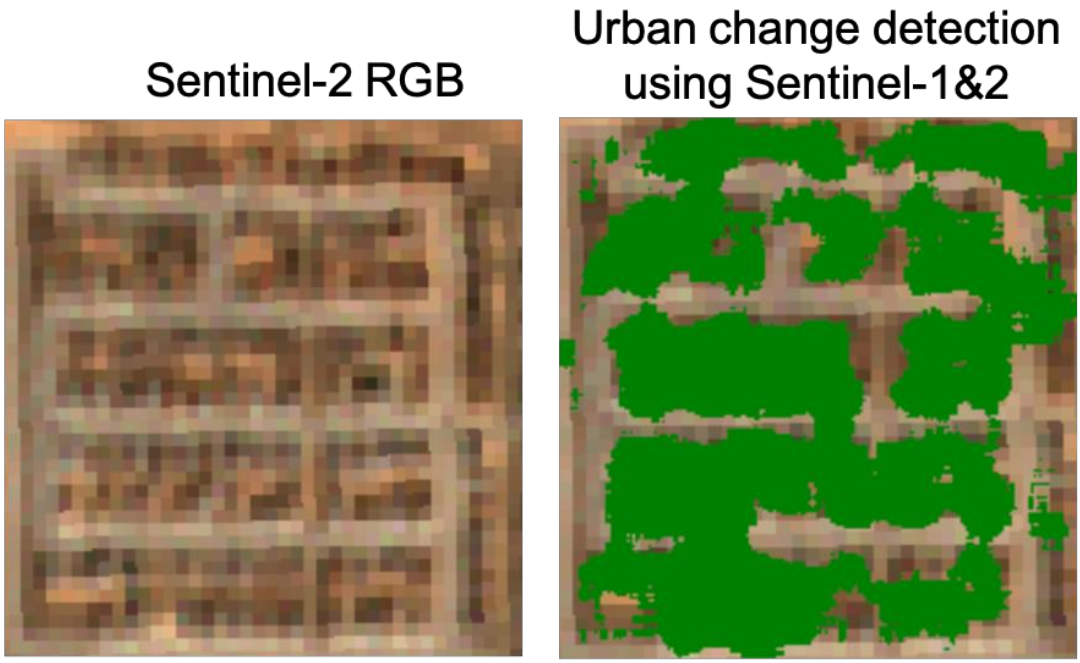

Figure 11: Detail of a new neighborhood. The classification of the newly built-up area with Sentinel-1 & Sentinel-2 shown in green

The developed algorithm is quite stable outside of the small validation area. Figure 8 shows the detection of newly built-up areas in the south-eastern part of Phoenix. The detection is similar to the test area, without any major false positives. This indicates that these methods can be a valuable tool in order to assess the change in urbanization on a bigger scale. Unfortunately, the testing and validation on a bigger scale was not feasible in the scope of this thesis.

As a manual classification of a ground truth is quite labour intensive and the method of validation itself is not the best, the test area is quite small. Another mode of validation would be useful in the future. A validation based on MODIS Land Cover data described by Mertes et al. (2015), was also considered, but the temporal data availability and resolution was not sufficient for a good comparison.

When looking at the classification results of Sentinel-1 in Table 2, it could be assumed that it is already better than the combined classification, but this could be misleading based on the used test area. When applying the same methods to a bigger scale other significant changes in the Sentinel-1 reflectance values could be encountered. These could be changes in water surface cover, like drying lakes or flooded areas (DeVries et al., 2020). Another possible source for big changes could be deforestation as described by Reiche et al. (2018). Because of phenomena like these, it is important to

include another approach, which explicitly only detects changes for built-up areas, like the Index based approach with Sentinel-2, described in this thesis.

For even better results in the same arid environment as Phoenix, a similar approach to an Index-based classification of urban areas has been done by Rouibah & Belabbas (2020). They found that an inclusion of another index, namely the Bare Soil Index, further improved their classification.

Applying the same methodology to another urban area in another climate zone would also be of value. As the change detection based on the Sentinel-1 data is quite general, the behaviour of the classification should be similar to the one in this study. For the complementing classification based on the Sentinel-2 data, thresholds could be easily refined for other areas with a more humid environment. But this could unfortunately not be done in the scope of this thesis.

In summary, whereas the application and validation of the proposed methods should be done on a larger scale and the methods themselves can still be further improved, this thesis showed that the approach of combining two independent classifications of urban change detection is promising and is already providing valuable results.

APPENDIX

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Additional Resources

The source code for the developed methods can be found here: https://code.earthengine.google.com/5fedbda82206a27fd0fc470a7ff5ae6b

Erklärung

gemäß § 15 Abs. 5 APO in Zusammenhang mit § 35 Abs. 7 RaPO

Name: Adolph

Vorname: Samuel

Geburtsdatum: 27.09.1994

Studiengang: Geoinformatik und Navigation

Studiengruppe: 7W

Matrikel-Nr.: 28011717

Winter-/Sommersemester: Sommersemester 2021

Betreuer/in: Prof. Dr. Michael Schmitt

Hiermit erkläre ich, dass ich die Bachelorarbeit selbstständig verfasst, noch nicht anderweitig für Prüfungszwecke vorgelegt, keine anderen als die angegebenen Quellen oder Hilfsmittel benutzt, sowie wörtliche und sinngemäße Zitate als solche gekennzeichnet habe.

München, 01.07.2021

Ort, Datum

Samuel Adolph

Unterschrift