Evaluating the Potential of Multispectral Satellite Imagery for Water Stress Assessment in Agricultural Vegetation

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ABSTRACT

For its large-scale and short-term properties multispectral satellite imagery plays a big role in drought risk assessment. Among the costliest and most difficult to handle due to lasting cascading effects and multiple trigger points, droughts affect human life directly. Assessment and monitoring are valuable practices to adapt to and mitigate further droughts. Two of the most important aspects of droughts are the vegetative moisture and vitality of crops since they indicate declining soil moisture and possible water stress. Based on satellite imagery the calculation of three distinct indices and quantification of vegetative properties, the NDVI for vegetation vitality, the REIP for chlorophyll content and the NDMI for vegetative moisture content, becomes possible. By comparing all three indices together, information about the type of stress and hence adaptation and mitigation possibilities become available. To be able to compare the results over the years between 2018 and 2022, which include non-drought and drought years, fields with the same crop species and suitable cloud-free satellite imagery had to be selected. Therefore, using a QGIS model, this study evaluates the three indices for two study areas near Würzburg, Germany. In a monthly analysis, a decrease in the vitality and in moisture content especially in 2022 match climate data and the claims of local farmers that 2022 was a very dry year with much less yields. The NDVI and NDMI together show good first indicators for water stress in crops and thus can assist in the decision making of locals in terms of irrigation and fertilization. The REIP shows similar results as well, but at some times differs to a specific extent so as it becomes difficult to define trigger points with it. As a part of a larger context where multiple indices and indicators are included alongside ground truthing, this project shows an easy entry point for high-resolution water stress recognition and a basis for further research which is needed regarding the topic of drought assessment.

Keywords

Drought risk assessment, crop water stress, remote sensing, multispectral satellite imagery, vegetation indices, NDVI, NDMI, REIP

INTRODUCTION

Droughts are complex and globally occurring disasters which affect humans and nature alike. They are among the costliest disasters humans have to face for their large spatiotemporal extent and multilevel impacts, having lasting cascading effects as a consequence (Grillakis, 2019; Wilhite, 2000). The consequences depend on the type of drought for there are four main types which often concur, having different impacts on humans and nature (Heim, 2002).

Meteorological droughts are defined as a precipitation level below the regional normal average lasting longer than a specific regional defined time period. Due to the high variation of precipitation in different regions, definitions with absolute values for meteorological droughts cannot be used uniform worldwide (Wilhite and Glantz, 1985). This applies for the following droughts as well.

Linking to meteorological droughts, the decreasing soil moisture of the topmost surface layers containing the largest part of roots entail *agricultural droughts*, affecting humans indirectly but strongly with lesser yields and nature directly with a decrease in plant growth potential (AMS, 1997; Wilhite, 2000). Soil moisture not only depends on meteorological conditions, but on soil properties as well and therefore reacts differently to precipitation changes in different regions, rendering a uniform definition of agricultural droughts more difficult (Wilhite and Glantz, 1985).

Components of the hydrological storage system are used for multiple purposes and depend on the recovery of water stored in them through precipitation. Is the meteorological drought more severe, surface and subsurface water will be affected and as a consequence streamflow, groundwater, reservoirs and lake levels decrease. These drought impacts are defined as a *hydrological drought* (Heim, 2002). These are consequences with the potential to last "well beyond the end of the meteorological event because the recovery time for water stored in surface and subsurface systems is quite long in many cases" (AMS, 1997, p. 848).

A "drought develops slowly and impacts accumulate as conditions persist for seasons or years. Impacts are usually first apparent in agriculture, but gradually ripple to other sectors such as transportation, energy, recreation and tourism, and urban water supplies" (AMS, 1997, p.848). The reduction of streamflow has an impact on the economy because economic goods which depend on enough flowing water cannot be shipped accordingly. Furthermore, the distribution of drinking water is directly affected due to the decrease of groundwater levels, having strong direct impacts on humans. These impacts are defined as *socioeconomic droughts*, directly affecting the economy and social life (AMS, 1997; Heim, 2002; IPCC, 2018).

Due to Climate Change as we are experiencing it today, more frequent and longer-lasting droughts are anticipated in different regions on earth, even in Central Europe which so far was not impacted by droughts as much as other regions on earth (De Brito et al., 2020; Grillakis, 2019; Kloos et al., 2021). In order to adapt to the changes as early as possible, indicators have to be analyzed and trigger points defined (Thober et al., 2018). Due to the complexity of droughts, there are different types of indicators for when droughts occur, given the potentially fast-changing meteorological conditions and distinctive soils with different features in different regions (Heim, 2002; Wilhite and Glantz, 1985). To better understand how droughts form and what factors are included one large part of evaluating droughts is the analysis of water stress of crop vegetation. This is the part which affects humans most noticeable and gives the first indication on an agricultural drought which itself hints towards hydrological or socioeconomic droughts possibly occurring later on (AMS, 1997; Heim, 2002).

A tool to provide fast, large-scale and short-term information on multiple regions at once are indices calculated with multispectral satellite imagery (Kloos et al., 2021). There are many studies already using different indices derived from satellite imagery to analyze past drought events and evaluate those indices (Erfurt et al., 2020). WMO and GWP (2016) furthermore show many different indices and indicators for drought monitoring in their "handbook of drought indicators and indices". Many of them use different types of data like meteorological data or soil property data to quantify one of the multiple aspects of droughts as mentioned before. Additionally, most of them have in common that they do not show direct drought events but rather hint towards them (Ghazaryan et al., 2020).

Out of 50 total entries only four are for the monitoring of soil moisture and only ten are using satellite data. The rest depends on multiple datasets other than remote sensing data and often try to enhance other indices and indicators by including further data. Vegetative moisture or soil moisture indicators are not described as easy to obtain and often are too unspecific or complex so as to not being suitable for a first indicator of an occurring drought (WMO and GWP, 2016). Not one of the ten indicators which use satellite data have the possibility to provide a high resolution under 50 meters or are easy to use as to be useful for small extent drought monitoring.

In addition to the listed indices there is an index, the Normalized Difference Moisture Index (NDMI), which is based on the Normalized Difference Water Index and according to Xu (2006) and Jin and Sader (2005) aims to show the moisture content in plants with a high spatial resolution depending on the satellite imagery. It is not listed in the handbook of WMO and GWP (2016) as a possible index for the quantification of moisture, a large component of drought monitoring. But it is included for example in the widely known Sentinel Hub EO Browser operated by Sinergise and used as a direct indicator for vegetative moisture and an indirect indicator for soil moisture for example in Jin and Sader (2005).

The aim of the project is to evaluate two common indices and the NDMI derived only through openly accessible satellite data for their responsiveness to drought symptoms. The other two indices are used for the analysis of chlorophyll content (Red-Edge Inflection Point, REIP) and biomass estimation (Normalized Difference Vegetation Index, NDVI) and are mentioned in multiple studies in the context of agricultural drought detection (Aryal et al., 2022; Ghazaryan et al., 2020; Kloos et al., 2021; Noack, 2018). These indices could be included in a toolset which enables the automatic calculation of trigger points for droughts and therefore help in the adaptation and mitigation of droughts. The toolset has to be available to locals including farmers who through this are able to adjust fertilization and irrigation for adapting to the drought event and protect components of the hydrologic storage system trying to mitigate further hydrological or socioeconomic droughts (Ghazaryan et al., 2020).

SPECTRAL REFLECTANCE AND INDICES

Remote sensing is widely used for drought assessment and monitoring vegetation or crop conditions. Based on certain spectral properties of vegetation different indices can be calculated, which provide information on plant vitality, biomass, chlorophyll content and also moisture content. The spectral properties of different objects are based on the fact that every object absorbs and reflects different wavelengths (parts) of light (Hadoux, 2014). Figure 1 shows the ideal-typical spectral reflections of different objects on the ground in regard to the wavelengths of the visible light and longer wavelengths. It is clearly observable that there is much more information in the reflectance of the longer wavelengths than in the visible light. To show such information, multispectral imagery is needed which captures the light at multiple wavelengths. The distinctive reflectance curves of the objects can hint towards the type of object which is present in multispectral satellite images and therefore can be used as a classification method without actually evaluating every object on the ground by hand (Jensen, 2007).

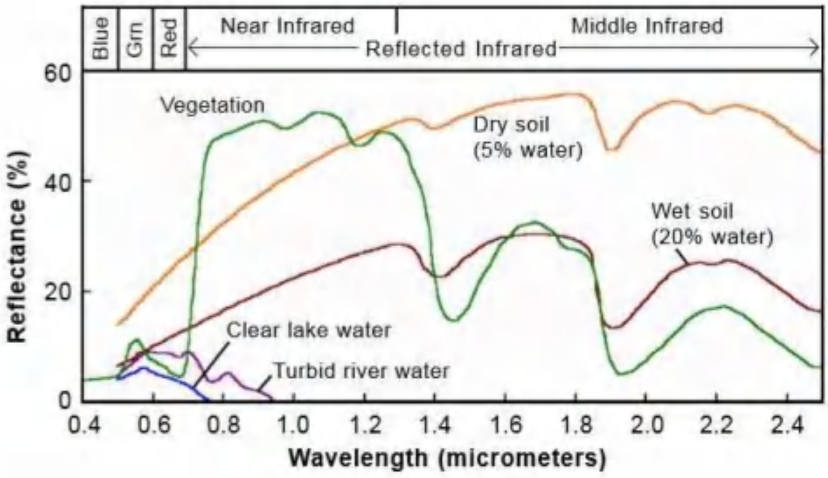

Figure 1. Spectral reflections of different ground objects (adapted from Mondal, 2018).

Especially vegetation has a very distinctive course in its reflection for it highly absorbs light in the blue and red wavelengths of around 490 and 665 nanometers, reflects some light in the green wavelengths of around 560 nanometers and strongly reflects light in the near-infrared (NIR) range of around 835 nanometers, not visible to the human eye (ESA, 2022; Gross, 2005). That is because of pigments in the leaves which react with sun light during the photosynthesis process. Chloroplasts in the leaves, cell-like structures which contain a high amount of chlorophyll, absorb the light in the blue and red wavelengths (as seen in Figure 1) and reflect parts of the light in the green wavelengths. That is why the leaves are seen as green, they mostly reflect the green wavelengths back to our eyes (Gross, 2005; Reckleben, 2014).

This changes with the age of vegetation and their condition regarding moisture and nutrients as seen in Figure 2. The concentration of chlorophyll decreases and the lesser reflection of the red bands by carotenoids gets more prominent, therefore leaves seem to get redder and even brownish (LPIMIC, 2022; Reckleben, 2014). In addition to that the cell walls inside the leaves scatter and reflect a large amount of the light in the NIR due to its low interaction with chlorophyll. This is the reason why the reflection value of healthy green vegetation in the NIR is so high and how the distinct reflectance curve forms (Gross, 2005). Due to this fact the concentration of chlorophyll in leaves, in other words the greenness of them, can show the health status of vegetation and hint towards stress of different kinds. But the density of the leaves and therefore the absolute biomass can alter those measured values as well, so it is advised to always keep in mind that the spectral reflection values can change during the growth phase and its condition based on different factors (Jensen, 2007; Lilienthal, 2014; Reckleben, 2014). The low reflection in the wavelength of mid infrared is caused by water that is stored in the plants and can therefore give information on the moisture content and water stress of vegetation (Hadoux, 2014). All these characteristics in the behavior of reflectance of vegetation can be used to calculate different spectral indices. In this study we calculate the Normalized Difference Vegetation Index, the Red Edge Inflection Point and the Normalized Difference Moisture Index.

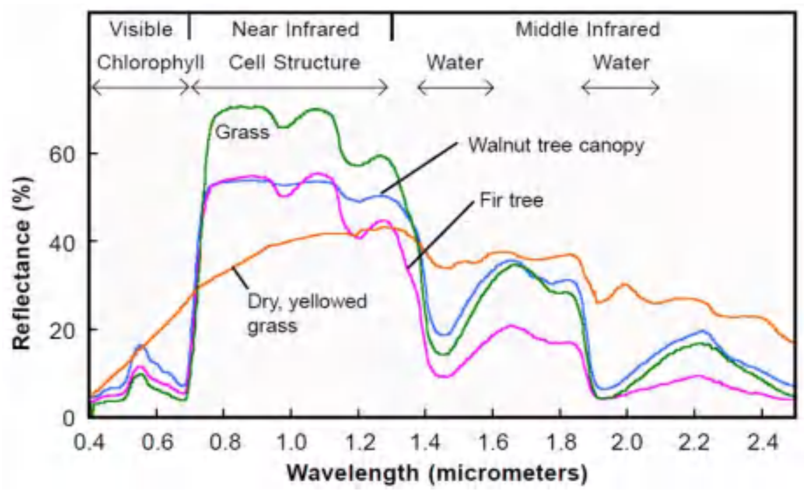

Figure 2. Spectral reflections of different vegetation objects depending on their water content (adapted from Hadoux, 2014).

Vegetation vitality with NDVI

The difference in the distinctive reflection between the red and NIR bands as seen in Figure 1 is very useful when classifying and distinguishing vegetation from other objects using for example the NDVI, which commonly is used in remote sensing analyses including different kinds of vegetation (Candiago et al., 2015; Jensen, 2007). The index can be calculated by using the mentioned wavelengths with following formula:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

(adapted from Rouse et al., 1974)

The calculation results in a value range of -1 to 1 which shows the photosynthetic activity of plants and therefore their health status or vitality respectively (Jensen, 2007). Lower values below zero indicate the absence of vegetation, higher values above zero and towards one show increased photosynthetic activity and therefore a higher biomass (Aryal et al., 2022; Candiago et al., 2015). This index can be used to evaluate the NDMI because of its ability to show differences in the vitality of vegetation and its biomass, possibly caused by water stress and therefore correlating to the results calculated with the NDMI and the chlorophyll content calculated with the REIP.

Chlorophyll content with REIP

The shift in reflection between 670 and 770 nanometers from low values for the red wavelengths and high values for the near-infrared wavelengths is called "red edge". The position of this turning point of spectral signature can change due to chlorophyll content, age of the plant and Leaf Area Index (LAI). The LAI provides information about the leaf area per soil area and therefore about the quantity of leaf layers (Lilienthal, 2014). During the growing stages of vegetation, the inflection point usually moves from short wavelength to longer ones. But also impacts like diseases, water stress or low nitrogen content can alter the position and would cause a movement to a shorter wavelength (Lilienthal, 2014). In this study the REIP is used to investigate the chlorophyll content and also the vitality of vegetation. Due to water stress, we would assume a shorter wavelength for the position of the red edge inflection point. It is calculated as follows:

$$REIP = 705 + 40 * \frac{\frac{\rho_{670} + \rho_{780}}{2} - \rho_{700}}{\rho_{740} - \rho_{700}}$$

(adapted from Guyot et al., 1988)

Moisture content with NDMI

Calculating the NDMI is possible due to the spectral difference between the NIR and the short-wave infrared (SWIR) wavelengths. The usually low reflection of water has a stronger effect when the vegetation is healthy having a higher water content (Hadoux, 2014). Due to this the three distinct incisions at wavelengths 1450, 1900 and 2500 nanometers are formed as seen in Figures 1 and 2. Based on the NDWI by McFeeters (1996), which tries to maximize the reflection of water by using the green band and "minimize the low reflectance of NIR by water features" (Xu, 2006, p. 3026), the NDMI is not computed to show open water, but rather show water inside vegetation since it uses the spectral differences between the NIR and SWIR due to the influence of water content (Wilson and Sader, 2002). Therefore, it seems suitable to analyze vegetative moisture, which could help to show water stress in crops early on and enable the early adaptation to or mitigation of droughts (Jin and Sader, 2005).

The index can be calculated with following formula:

$$NDMI = \frac{NIR - SWIR1}{NIR + SWIR1}$$

(adapted from Wilson and Sader, 2002)

The index results in a -1 to 1 value range as well which quantifies the spectral minimization by the water content in vegetation (Xu, 2006). The higher the value, the higher the water content in the object. Values under zero hint towards low contents of water. The water content in the vegetation can provide an indirect indicator for soil moisture since the moisture in vegetation derives from the soil, so the NDMI can be useful when analyzing stress situations and should correlate with the NDVI and REIP (Jin and Sader, 2005; Wilson and Sader, 2002).

MATERIALS AND METHODS

Study area

Figure 3. Overview of the study areas 1 and 2 (own representation).

For the investigation of crop water stress two agricultural fields were selected as study areas. The fields are located near the village of Prosselsheim in Bavaria. Figure 3 gives an overview about the specific locations. The whole area surrounding the two sites is highly cultivated, the dominant crop is winter wheat, but also corn, sugar beets, rapeseed and spelt are grown. This region reaches from northeast and east of the city of Würzburg to the Main River and the so called Mainschleife, where vine is the predominant crop.

Study area 1 is a field of 2,92 hectares in size and is named "Wachtelberg", study area 2 is larger with 4,47 hectares and is called “Zwölf”. According to the soil map provided by the Bavarian Ministry of Environment (LfU), the soil of study area 1 is classified into different soil types. The part near the stream consists of a calcareous colluvial gley that formed on top of loam and clay, the upper northeastern part is a rendzina on top of silt and clay. In contrast to that study area 2 is completely classified as luvisol, developed out of silt and silty clay, making it more fertile than study area 1 (UmweltAtlas Bayern: ÜBK25).

The mean precipitation amount for the climate normal 1981 to 2010, measured at the climate station of Würzburg, is 596,1 millimeters per year. The precipitation maximum is in July, the minimum in September (DWD, 2022). The investigation period of both fields was 2018 to 2022 at which area 1 was cultivated with corn four times (2022, 2021, 2019, 2018), area 2 three times (2022, 2021, 2019).

Data

There are and were many satellites in orbit around earth providing multispectral imagery for different purposes with different resolutions and bands. That is why it is advised to choose a dataset beforehand based on the needed requirements. The data should be openly and freely accessible and still have a high resolution in the needed bands. As stated in Aryal et al. (2022) and Isioye et al. (2020) one of the preferred datasets is the Sentinel-2A data provided by ESA, openly accessible through the Copernicus Open Access Hub (*https://scihub.copernicus.eu/*), since it has a higher resolution in the respective bands of 10 to 20 meters than other prominent datasets like Landsat 8 with 15 to 30 meters and MODIS with 250 meters to 1 kilometer (ESA, 2022; NASA, 2022a; NASA, 2022b). With a swath width of 290 kilometers and a radiometric resolution of 12-bit the system provides geometrically and atmospherically corrected bottom-of-atmosphere reflectance values with a high temporal resolution of five days. The sensor system is able to record wavelengths at 13 different bands from visible to short wave infrared and also supplies accurate bands in the spectral part of the red edge (ESA, 2022). These bands are needed to calculate the different vegetation indices that are used in this study.

After registering and creating an account at ESA an intuitive selection of data for a specific region of interest (ROI) and time period becomes available on the Copernicus Hub. The largest problem with optical satellite data is the cloud coverage since clouds limit the available multispectral data (Aryal et al., 2022). That is why it is advised to limit the cloud cover of the satellite images to 0 to 10% and look closely at every raster image to ensure the ROI is cloud free before downloading the data. Automatically downloading such raster images can lead even with the cloud coverage settings to uncontrollable value errors, that is why during our project no automatic downloading of raster data was pursued. In this study satellite images of the years 2022, 2021, 2019 and 2018 were used. Moreover, several images per year were selected. To get cloud free imagery the timeframe for the images of a single year was set broadly but narrowed down if possible.

The evaluation and comparison of the three indices can only be meaningful if done on specific vegetation over a specific time period, therefore according datasets have to be created. As vegetation cover, corn was chosen to investigate the impact of the dry summer months in 2022 on crop water stress. Following the growing stages of the plants, satellite images were selected at three different timesteps within a year, Mid-June, Mid-July and Mid-August. As mentioned above the timeframe was set broadly to get cloud free images. The image with no cloud coverage that was closest to the 15th of each month was selected and used to calculate the different vegetation indices. Thereby it was possible to extract eleven images out of the four years under investigation. By comparing the images of the different years at a certain timesteps we were able to analyze the reaction of each index to different crop conditions which are known to be most likely caused by water availability.

Method

The project is structured in three major steps: 1) calculating the indices with the QGIS model and generating statistics, 2) quantifying the crop vitality and water stress with the results and 3) evaluating the indices with the help of data regarding drought events. The workflow of the methodology can be seen in Figure 4. A similar methodology can be seen in other studies with related topics as well (Erfurt et al., 2020; Ghazaryan et al., 2020; Kloos et al. 2021). Depending on the topic of the studies they are including other indices and data as well to focus on specific aspects of droughts.

The largest part of the workflow is the QGIS model as seen in Figure 5 since it is used to preprocess the input files and calculate the indices along with their statistics. It is structured in three main parts as well: first it takes the input data and clips the raster files with the shapefiles to the study areas to minimize calculation time and to provide valid datasets for evaluation. Because three indices that require different bands were used, a total of six raster files have to be read per run and every raster band has to be read and clipped individually which takes the longest calculation time. After preprocessing the files, the indices are calculated by using the SAGA Raster Calculator (SRC). Other options are available like the raster calculators from GDAL and GRASS, but empirically

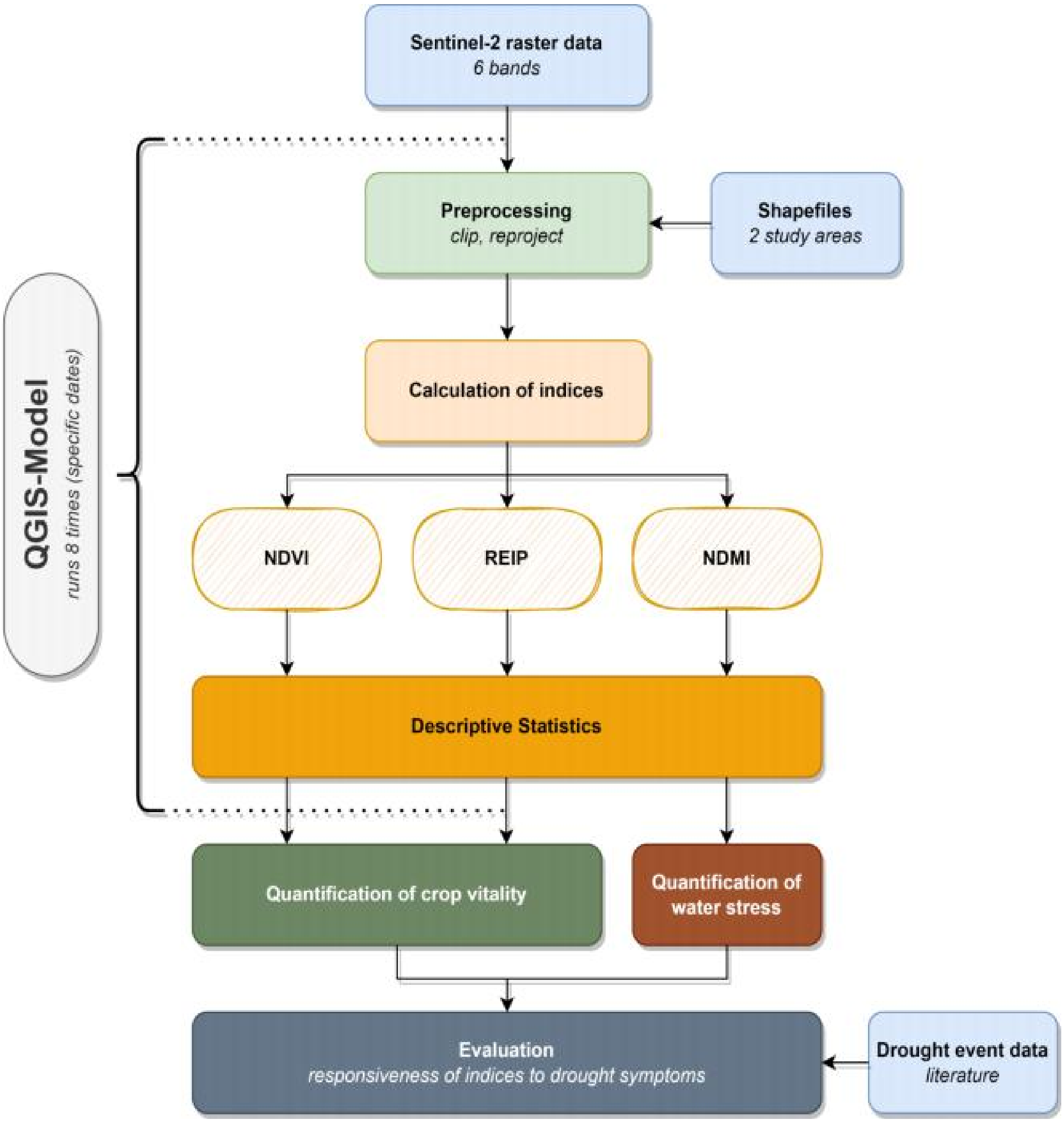

Figure 4. Workflow of the project. Light blue elements are inputs, the other elements are either calculated using the QGIS model or statistical software. The QGIS model has to be run eight times because there are eight specific time points where the crop vitality and water stress are quantified (own representation).

only the SRC did always provide valid outputs and could be implemented into the model without further issues. Moreover, the QGIS model is able to create zonal statistics of each algorithm output of the SRCs, meaning one statistic output per index. The statistical mean, minimum, maximum, sum and count are generated and used to describe yearly differences in the values of each index. The raster files of the calculated indices and the derived statistics are saved individually as outputs. The QGIS model makes the workflow of the study transparent and repeatable for other study areas and cases. Furthermore, it gives the opportunity also for non-GIS-experts to calculate different vegetation indices using satellite data, because only the inputs have to be selected, while all outputs are generated automatically and can then be analyzed. The goal of this study thereby is to evaluate the different vegetation indices regarding their responses to water stress of vegetation. The model could be used to define trigger points by analyzing an appropriate time series of several years for each study area, when it was cultivated with a specific crop (in this case corn) and calculate a mean value for each pixel and index.

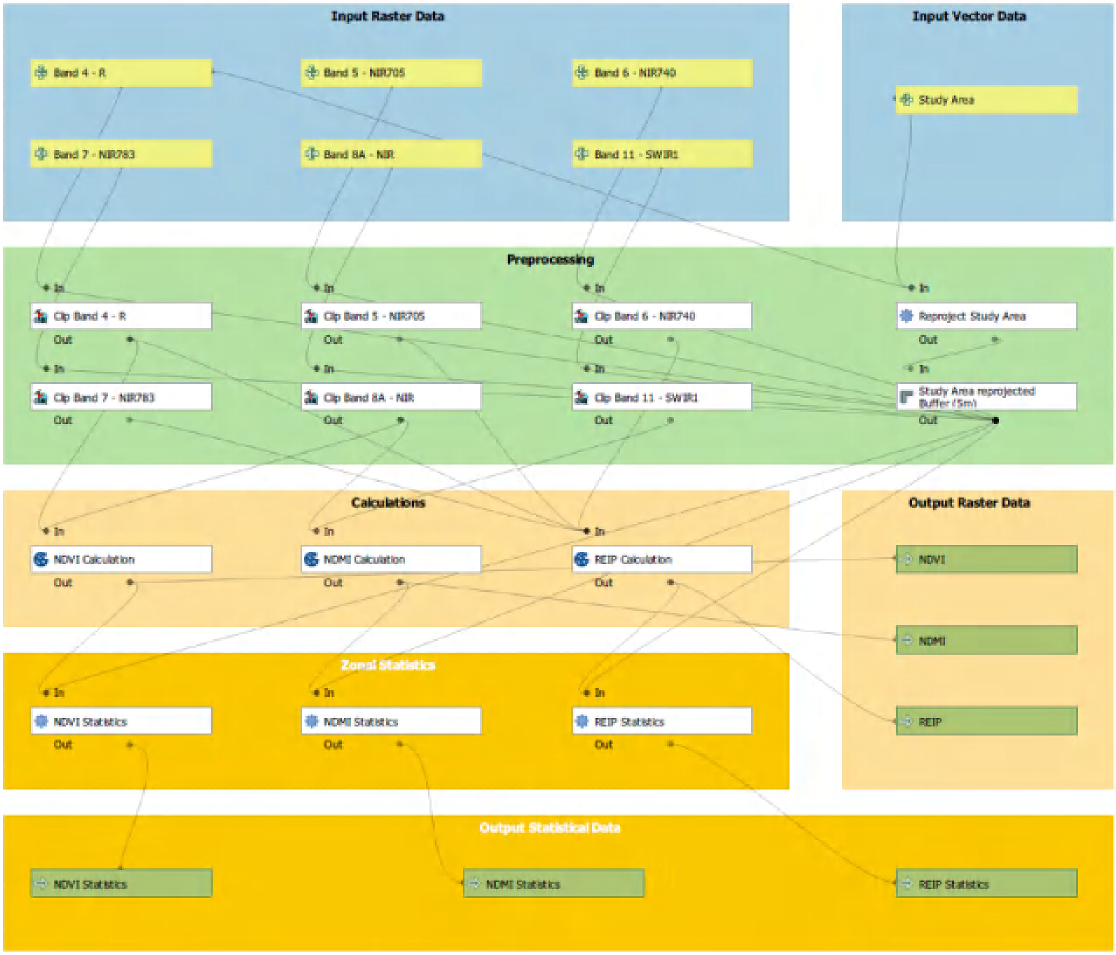

Figure 5. QGIS model. A larger view can be found in the appendix (own representation).

RESULTS

In the following chapter the results of the calculation of the vegetation indices are presented. At first study area 1 is described, followed by study area 2. For each area the NDVI, the REIP and the NDMI were computed based on Sentinel-2 imagery.

Study area 1

The results of the different indices for study area 1 show good accordance. Starting with the NDVI it detects low values of less than 0.4 for every year at the timestep of Mid-June, suggesting a very low vegetation cover. Only in 2019 the values are above 0.6 for almost the whole field. In July the NDVI has high values in the years 2019 and 2022, lower values in 2018 and compared to the other years extremely low ones in 2022. This tendency is sustained in August (Figure 6).

Comparing the values of the NDVI in Mid-July to these of the other indices NDMI and REIP, we can see good accordance especially for the NDVI and the NDMI. Both indices show similar spatial anomalies of their values. In 2018 the Middle of the field is detected as a zone of high values in all three calculations. Thereby NDVI and NDMI also show high agreement in the single pixels of the image regarding their high and low values. In 2019 and 2021 all indices detect high values for the whole area, whereas in 2022 much lesser values are calculated. The NDVI is below 0.6 for the south-western part of the field and even below 0.4 for the north-eastern part. The values of the NDMI show equal spatial distribution and range from 0.3 to less than 0. That indicates a less vital and stressed vegetation cover. The REIP shows some differences in its values. Equally in the south-western part the values are higher, but the anomaly reaches more north-east wards at the top of the field and therefore disagrees with the trends NDVI and NDMI detect (Figure 7).

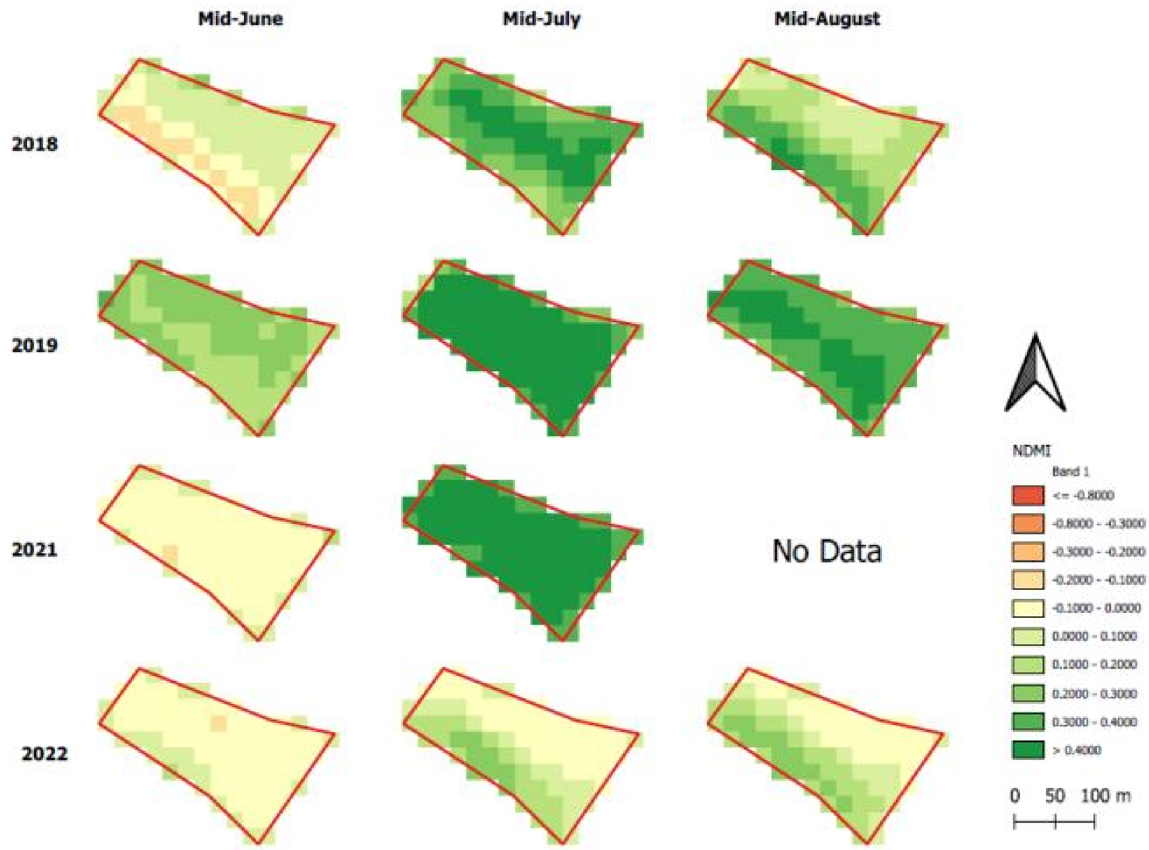

Figure 6. Spatial distribution of NDVI values within study area 1 for different years at Mid-June, Mid-July and Mid-August (exact image dates: 06.06.2018, 19.07.2018, 18.08.2018, 19.06.2019, 16.07.2019, 18.08.2019, 13.06.2021, 18.07.2021, 15.06.2022, 18.07.2022, 12.08.2022, own representation).

Having a closer look at the values of the indices in Mid-July, the trend described above is also clearly visible. In 2019 and 2021 the average values are highest. The NDVI has an average of 0.85 in both years, the NDMI around 0.45 and the REIP around 732. In 2018 and 2022 the values are much lower. Especially in 2022 there is a dramatic decrease in the average of the NDVI and the NDVI, falling down to 0.30 (NDVI) and 0.05 (NDMI, Table 1). That means a trend downwards of about 65% for NDVI and even about 88% for NDMI compared to the values of 2019 and 2021. In contrast the REIP falls only to 725.22 and therefore is not showing this dramatic decrease in its mean value, suggesting this index to be less sensitive for detecting crop vitality due to water stress.

Table 1. Average values of NDVI, NDMI and REIP on study area 1 for the years 2018, 2019, 2021 and 2022 at Mid-July (for exact image dates see figure 6; own representation).

Index	2018	2019	2021	2022
NDVI	0.74	0.85	0.85	0.30
NDMI	0.33	0.45	0.44	0.05
REIP	728.79	731.04	732.49	752.22

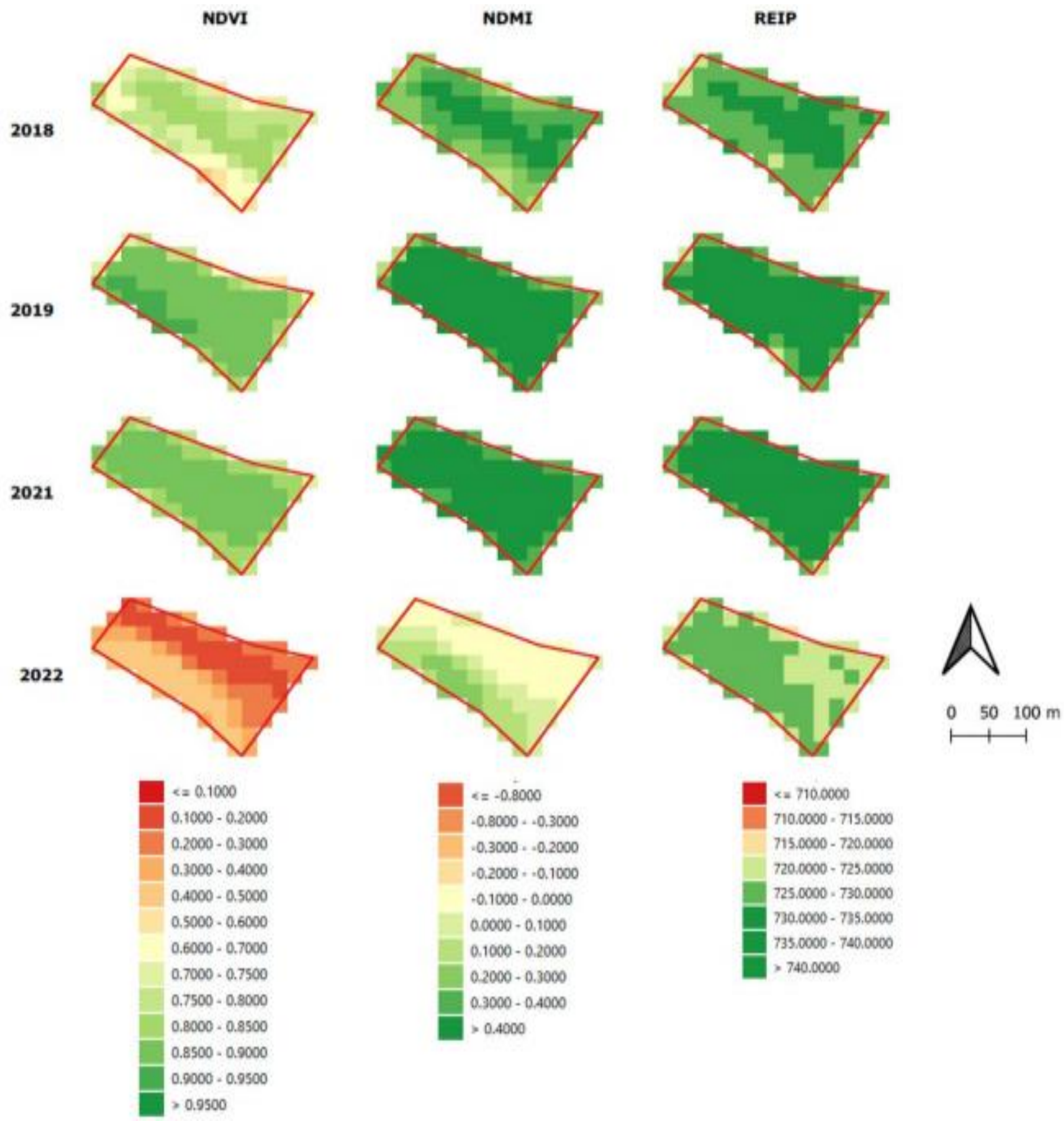

Figure 7. Comparison of NDVI, NDMI and REIP on study area 1 for different years at the time of Mid-July (exact image dates: 19.07.2018, 16.07.2019, 18.07.2021, 18.07.2022; own representation).

Study area 2

In the case of study area 2 the tree indices were calculated for the years 2019, 2021 and 2022. As for study area 1 the different calculations show good accordance. At Mid-June the values of NDVI are also low, but rising to Mid-July, before slightly falling to Mid-August for the years 2019 and 2022. For the NDMI and REIP this trend is also visible (Table 2).

Table 2. Average values of the different vegetation indices and study area 2 at several timesteps for the years 2019 and 2022 (for exact image dates see figure 6; own representation).

	Mid-June		Mid-July		Mid-August	
Index	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**
NDVI	0.67	0.27	0.87	0.47	0.84	0.40
NDMI	0.22	0.02	0.49	0.20	0.42	0.14
REIP	726.66	723.35	733.71	724.85	732.93	719.35

Comparing the different indices at the time of Mid-July it can be seen that the values of all three indices are very high in 2019 and 2021, indicating a healthy and well supplied vegetation. In these years almost no differences in crop conditions can be seen within the field. In contrast to that the calculated values are much lower in 2022. Also, disparities within the area can be seen. NDVI and NDMI show again good accordance detecting higher values in the centre of the field and lower ones at the boundaries. The REIP again differs from that trend by pointing out different areas with high values (Figure 8).

In Table 3 the average values of the different indices for study area 2 in Mid-July can be seen. While the years 2019 and 2021 have high mean values and show good accordance, the year 2022 strongly deviates from that. For this year the means are 0.47 (NDVI), 0.20 (NDMI) and 724.85 (REIP). Like in study area 1 especially the NDVI and the NDMI experience a noticeable decrease. For the NDVI it is about 55%, for the NDMI about 41%. The decrease of the REIP is slighter, again suggesting this index to be less sensitive for the detection of crop moisture.

Moreover, interesting observations can be made by comparing the results of both study areas. The mean values of the years 2019 and 2021 are quite similar for both sites around 0.85 (NDVI), 0.46 (NDMI) and 725 (REIP). Nevertheless in 2022 differences can be seen between the fields. The NDVI and NDMI have a clearly higher mean value on study area 2 indicating more biomass and less water stress than on study area 1. In contrast to that the REIP shows slightly higher averages on study area 1, suggesting that the REIP index is not linked to the NDVI and NDMI and therefore does not strongly correlate to biomass and water content of crops.

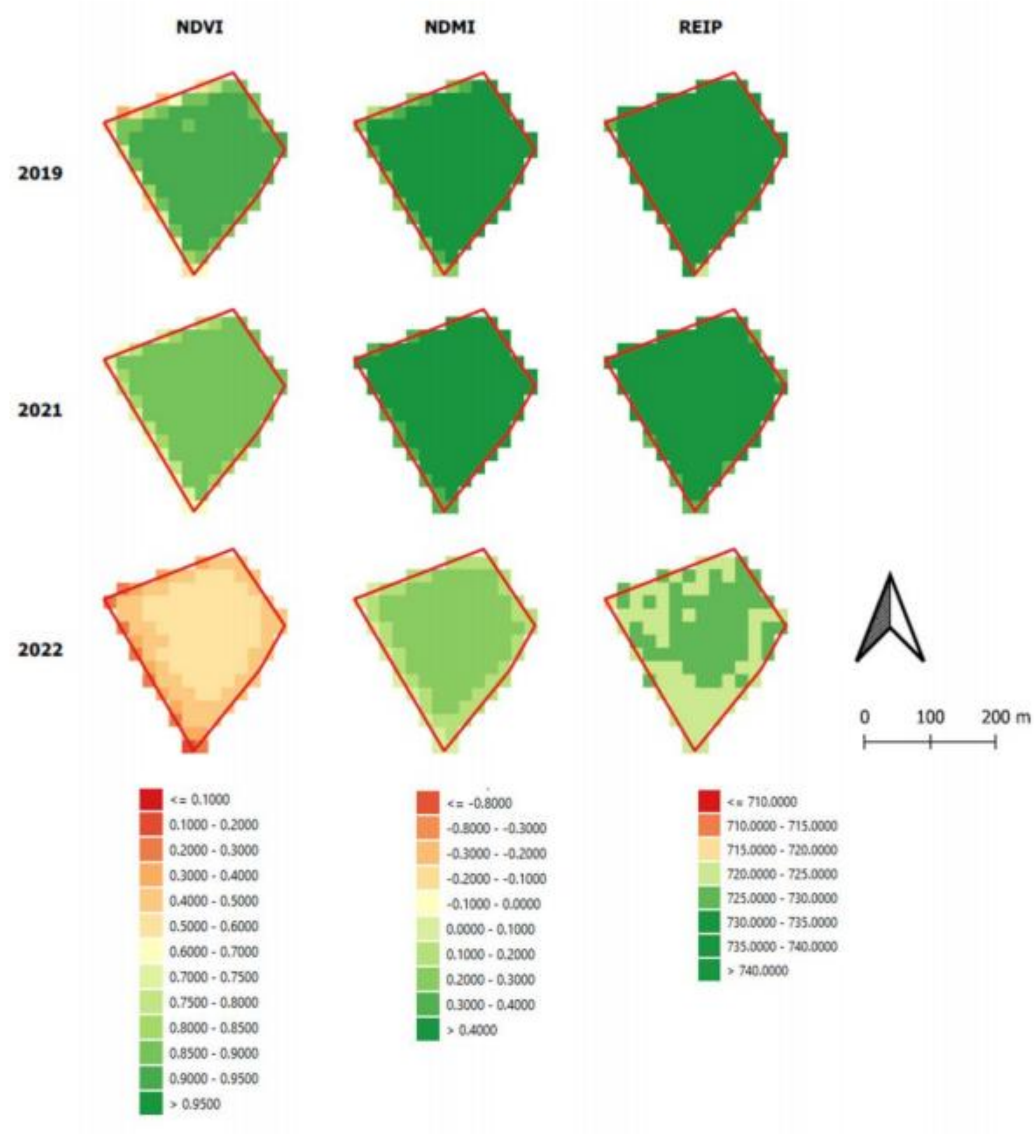

Figure 8. Comparison of NDVI, NDMI and REIP on study area 2 for different years at the time of Mid-July (exact image dates: 16.07.2019, 18.07.2021, 18.07.2022; own representation).

Table 3. Average values of NDVI, NDMI and REIP on study area 2 for the years 2019, 2021 and 2022 at Mid-July (for exact image dates see figure 8; own representation).

Index	2019	2021	2022
NDVI	0.87	0.86	0.47
NDMI	0.49	0.48	0.20
REIP	733.71	733.61	724.85

DISCUSSION

As both study areas are located close to each other, they show quite similar results. For both sites the different vegetation indices detected high values in 2019 and 2021, indicating vital and well supplied corn plants in good crop conditions. All three indices were able to observe less vital crop conditions for the years 2018 and 2022. Both years are known to have been extraordinary dry due to missing precipitation in the summer month. In 2018 the yearly precipitation was 432 mm and thereby much lower than the long term average for the region. Especially in the months September, October and November the rainfall was extraordinary low. In 2022 particularly the summer month June, July and August were much dryer than the mean calculated over 30 years. In these month only 80 mm of rainfall were measured, while the average sum is 175 mm. This becomes even more dramatic if we look at the exact dates of the rainfall. More that 50 mm fell at the beginning of June and at the end of August (data based on DWD Climate Data Center). Therefore the main growing period of corn which is between June and August was strongly affected by the absence of water.

The low values of the indices at Mid-June are most likely to be caused by the low vegetation cover due to the early growing stage of the corn plants. The higher values for this timestep in 2019 might be caused because of the later observation date on 19th of June or are caused by early sowing in this year. In 2022 and to some extent also in 2018 study area 1 shows a maximum within field variability in crop conditions. In the north-eastern part the values are much lower than in the south-western part. An explanation of this is the location of the field at a hillside, with the north-eastern boundary being on top of the slope. Moreover, the different soil types might result in different water storage capacity. The south-western part is also right next to a small stream that is retained by the dam of a beaver, leading to a high water supply in this area. The slope can therefore be considered much more vulnerable to water stress. In contrast to that study area 2 is more uniform even in the dry year 2022. That is caused by his homogenous location and soil type. The soil is most likely also the reason for the higher NDVI and NDMI values of the area compared to the other site, as luvisol is known to have a high water storage capacity.

NDVI and NDMI show a good accordance in every year. A reason could be the calculation of both indices, which is based on the NIR band. As also seen in the year 2022, it can be concluded that there is a correlation between water content and biomass for corn. In contrast the REIP shows some differences in the spatial distribution of its anomalies and also doesn't react as much as NDVI and NDMI on the drought in the years 2018 and 2022. Moreover in 2022 it observes a higher average value for study area 1 than for study area 2, while the NDVI and NDMI are clearly higher on study area 2. Therefore it can be suggested, that the REIP index is less sensitive on crop water stress than the other two and might rather give information on chlorophyll content and photosynthetic activity.

After consulting the local farmer these observations can be proven. Especially in the recent year 2022 he had to deal with much lesser corn yields and therefore supplement the loss by buying grain corn from merchants to be able to provide enough food for his cows. Thereby he had to denote economic losses in case of the absence of almost 50% of the yields and the money he needed to effort the additional food for his animals. In some cases such drought events can easily evolve from an agricultural to a socio-economic drought having a strong impact on the local population by causing financial trouble, loss of livestock, hunger and in the last consequence the loss of lives and livelihood.

This study shows how remote sensing can be used for water stress monitoring of crops and detection of water stress and drought events even in the early stages of plant growth. Therefore, it can enable the possibility for early action in strongly affected regions and mitigate the impact of such natural disasters. Moreover, it is an opportunity for farmers to adjust irrigation to the areas with greatest need even within single fields. The free availability of satellite images in combination with some basic GIS knowledge makes it a cost saving alternative to expensive commercial services. The QGIS model developed in this study can help farmers to implement such methods in their process of decision making.

Even though there are some limitations, which are mostly due to cloud coverage. Especially in years with high precipitation like in 2021 it can be difficult to find appropriate satellite imagery. Moreover, Sentinel-2 images are provided with a resolution of 20 meters which is not well suited for investigations on very small fields that are common in some countries. Therefore, it might be difficult to identify variabilities in stress of certain crops within single fields. Concluding, the data generated from satellite imagery can only be a help in the process of decision making for farmers and should never be used as absolute basis for decisions. Some indices like the NDVI often only show the impact of events on crops but do not point out the exact reason for low biomass and less crop vitality. That makes field work and ground truthing inevitably necessary.

There is also further work that needs to be done on this topic. Next steps could be the definition of trigger points for water stress to become critical for vegetation and yields in certain regions and for certain crop types. Best practice would be to calculate long term averages for each index on single fields or at least for regional areas and certain crop types. The model developed here could be used to calculate indices for several years and then average the results. However, an appropriate timeline of high-resolution satellite imagery is needed, which Sentinel-2 since its launch in 2015 can only provide to a limited extend. After that the monitoring of anomalies in the long-term average can be done for the years known to be affected by droughts and as a result defining the trigger points for further events, making early action protocols based on these values possible and contribute to the prevention of future drought impacts.

CONCLUSION

The study shows the potential of remote sensing for drought assessment and mitigation by crop monitoring through different satellite derived vegetation indices. According to our results the NDVI and NDMI are suitable as first indicators for droughts since they show the same severity of water stress in vegetation for very dry years. Alternatively, they show a high vitality and moisture of vegetation during agricultural favorable years, therefore showing a very good representation of the condition of the crops. The REIP usually detects similar trends, but because of the different spatial distribution of its anomalies and a different dimension of its values it is difficult to pinpoint the severity of the stress as it is possible with both the NDVI and NDMI.

Consequently, the NDVI and NDMI have proven valid for the detection of crop water stress and drought events. They are able to provide useful information for drought impact mitigation due to early actions in regions strongly affected by such events. Moreover they could help farmers adapt to possible ongoing dry conditions as long as the data is freely available and edited so as no high-level scientific background knowledge is needed to understand it. That is why they are suitable for the aim of the project, the possibility to do own drought analyses for locals. Nevertheless, the results of the evaluated indices cannot stand for themselves, but rather have to be proven by ground truthing through participation of locals like farmers. An approach could be to use a freely available app to enable participation in the analysis through measuring the soil moisture and vegetation vitality for a specific plot and comparing it to the automatically calculated NDVI and NDMI for that specific region. With this, the decision making for irrigation and fertilization can be assisted and made more cost efficient.

Due to their complexity, droughts need multiple indicators and indices to be recognized as such. This project is just a part of an ongoing scientific research of drought assessment but shows an easy entry point for remote sensing based, high-resolution water stress recognition and a basis for further research on the topic of drought assessment.

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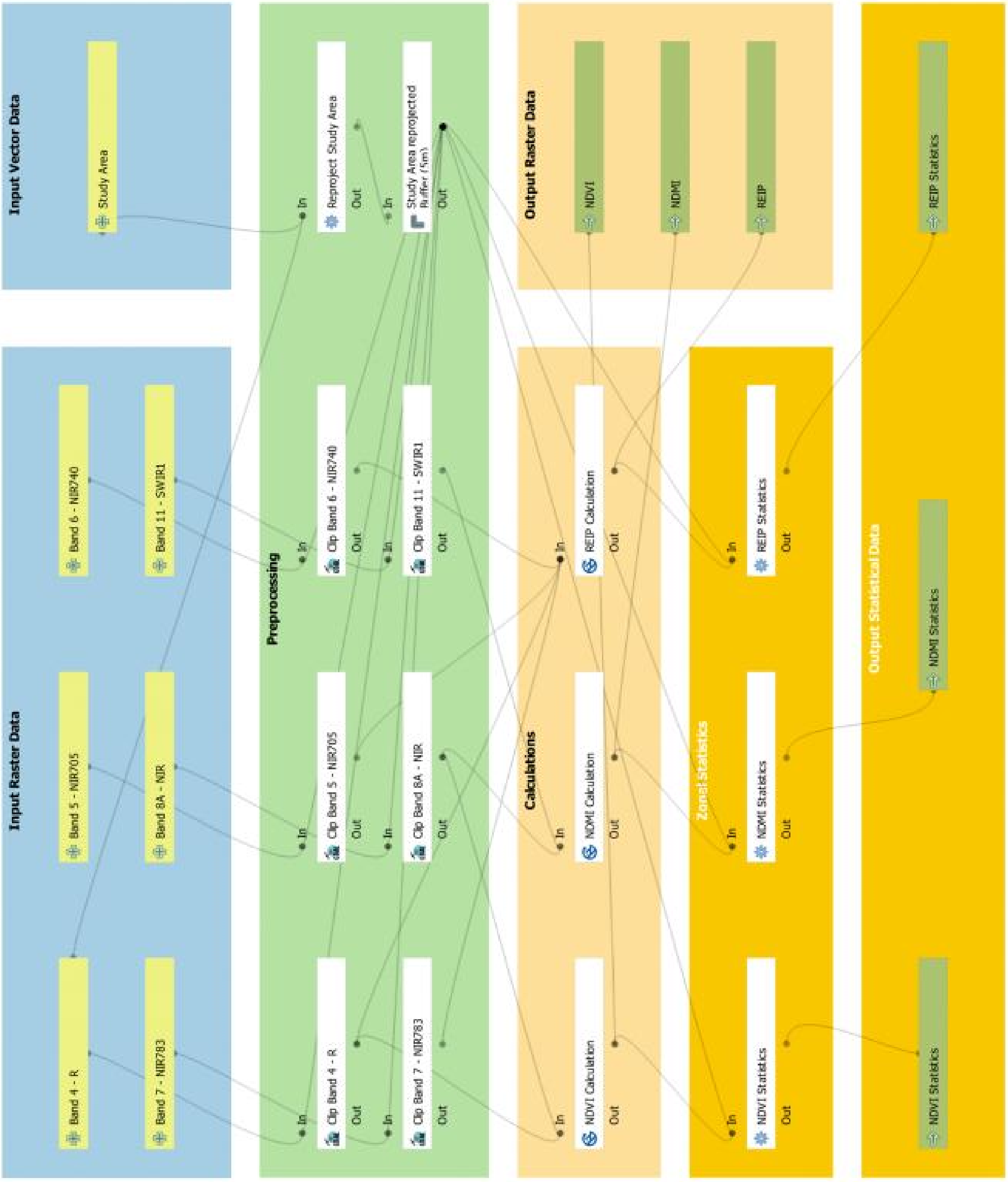
APPENDIX



Appendix. Large view of the workflow of project (own representation)