

INTERNSHIP REPORT

Determining the dryness index and evaporative fraction for satellite and drone images



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Internship report

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Summary

This project is part of the large TWIGA project, where our goal was to create a map that indicates the spatial pattern of an evapotranspiration product, based on an easy method and very little data. The area where this evapotranspiration product should be calculated for, is a drone image. These drone images were taken in Northern Ghana, close to Tamale. To come as close as possible to this evapotranspiration product, we calculated a dryness index and the Evaporative Fraction (EF). A very simple method to calculate a dryness index, where only the Land Surface Temperature (LST) and NDVI are used, is the triangle method. We created the triangle by using the LST and the NDVI pixels of the MODIS from an area located in Northern Ghana, for three different years. These three years are based on dry, wet and normal conditions to capture all the meteorological circumstances. The triangle is constructed based on two methods: one where the day LST is used and one where the difference between day and night LST is used. The dryness index (Temperature Vegetation Dryness Index (TVDI)) that results from the triangle is validated based on temporal and spatial correlation. It is concluded that the performance of the TVDI depends on time resolution and the specific location. Next, the TVDI and EF are calculated for the drone, where problems with difference in resolution arose. The triangle that we created was made with data which had a lower resolution compared with the drone. When using this triangle to calculate the TVDI of the drone, not all the details could be captured. Another problem was, the results of drone were difficult to check, because of little amount of available data. Therefore, more drone and field data should be gathered to better evaluate the outcomes of the drone and to create a triangle with a higher resolution.

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1 Introduction

1.1 Background

This project is conducted for the large TWIGA project. The TWIGA project is an EU horizon 2020 research project with the aim to gather geo-information on weather, water and climate for sub-Saharan Africa countries. This will be done by enhancing satellite-based geo-data with in-situ sensors and developing related information services that can help African stakeholders and the GEOSS community (*TWIGA Website*, n.d.). Within the large TWIGA project there is a working package that focusses on energy flux maps and time series (WP3.2). This project is linked to this working package by looking at the dryness index and the evaporative fraction in the Northern part of Ghana and using drone measurements which are made above a field close to Tamale.

With the Evaporative Fraction (EF) a closer look can be made at the evapotranspiration flux (ET). The ET indicates how much water is transported from the surface of the earth into the atmosphere. The EF indicates what fraction of the available energy is used for the ET and can be calculated with the following Equation (Stisen et al., 2008):

$$EF = \frac{ET}{R_n - G} \quad (1)$$

Here the R_n is the net radiation and the G is the soil heat flux. The EF gives a quick indication how high the ET is. An indication for the ET can be very important for a spatial overview of how much water the crops are using and where most of the water is used, which can be achieved with remote sensing. This is important for farmers, who have little water available for their crops, must apply their water as efficiently as possible. If it is known how much water the crops use for evapotranspiration, the water use efficiency can be increased.

For farmers it is best to know the spatial variation of the ET for their entire field. To create a clear picture of the ET on this scale, hydrological models could be used. However, this requires a lot of input data of different variables. In developing countries, with little infrastructure and just few monitoring sites which continuously measure environmental variables, it is a huge challenge to gather this data. In these regions, remote sensing can help mitigate the data scarcity issues. To increase the available amount of data, the TWIGA project was started and local drone measurements were made. The drone measured the land surface temperature and the NDVI and therefore we need a relatively simple method to calculate an indication for the ET.

The remote sensing method that requires the least amount of data is the triangle method. With the triangle method a dryness index is calculated, namely the Temperature Vegetation Dryness Index (TVDI). The TVDI indicates with a number between 0 and 1 how dry the soil is, based on the status of the vegetation and the surface temperature. If the TVDI is close to 1, the soil is dry and if the TVDI is close to 0, the soil is wet. A dryness index can be a good indication for the spatial variability of the ET. If a spot is dry you would expect a lower ET and if a spot is wet you would expect a higher ET.

With the triangle method, a triangle is created by plotting the Land Surface Temperature (LST) against the Normalized Difference Vegetation Index (NDVI), see Figure 1. The LST is the radiative skin temperature of the surface, which is measured with a remote sensing device. The NDVI gives an indication of the status of the plant, based on chlorophyll content, with a number between 0 and 1. Plotting the LST against the corresponding NDVI of an area with a lot of different vegetation types and soil moistures, a triangle will be formed. This shape is formed because when focussing on one specific NDVI, with lower LST, the soil should be wet which reduces the temperature. With the same NDVI, but now

with a higher LST, the soil should be dry which increases the temperature. This effect increases when more bare soil is present and decreases when the soil is more covered with vegetation and forms a triangle.

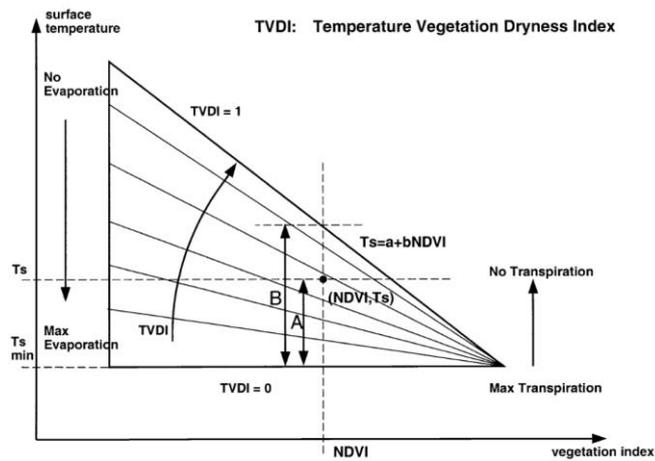


Figure 1 The triangle method where the LST is plotted against NDVI. The isohypse indicate the TVDI (Sandholt et al., 2002)

This triangle has two important edges, the wet edge at the lower boundary and the dry edge at the upper boundary (see Figure 1). The dryness of a certain pixel can then be determined by looking where the NDVI and the LST of that pixel is located relative to the wet and dry edge. If the pixel is located closer to the dry edge (point B) it has a higher dryness index compared with a point that is less close to the dry edge (point A) (Sandholt et al., 2002).

The triangle method is already been tested intensively, with promising results (Patel et al., 2008; Stisen et al., 2008; Tang et al., 2010). However, most of these studies calculate for every period a new triangle, which takes a lot of time. To decrease the processing time, we will try to make a universal triangle that includes all wet and dry conditions and can be used all the time. With this triangle we can then calculate the TVDI and eventually the EF for drone and satellite images for a specific area in the northern part of Ghana. To achieve this, the following objectives are formulated:

1.2 Objectives

- Make a universal triangle for the northern part of Ghana
- Calculate from this universal triangle the dryness index for the satellite and drone images and look at the resulting pattern.
- Calculate the EF from the universal triangle for the drone images.

2 Methodology

2.1 Study area

During this project we focused on the northern part of Ghana. In this area, drone images are made above an agricultural field close to Tamale (9°24'01.7"N 1°00'06.4"W). At the time the drone images were made, the field itself consisted out of small crops (cowpeas), but the ground was mostly bare. Figure 4 shows how the field looked like. This location will be our focus point throughout this project. However, to use the triangle method we need a larger area with more variation in vegetation cover and soil moisture to create a clear triangle and define the right edges. If combinations of LST and NDVI are missed, a part of the triangle could be missed, and the edges could potentially be wrongly defined. Therefore, we extended the study area to a larger part of Northern Ghana. The larger area is located between the coordinates: [(9°09'50.8"N 1°42'23.7"W), (10°00'27.8"N 0°27'29.8"W)] and is shown in Figure 2.



Figure 2 The location of the study area.

The climate in Ghana is tropical, where the North is the driest and hottest part. Here the annual amount of rainfall is 1000mm and the annual average temperature is 28.9°C. The landscape consists mainly out of Savannah with sparse agriculture (MoFA, 2016).

2.2 Data sources

The data used during this project is derived from a drone, an in-situ meteorological station and satellite images.

2.2.1 The drone

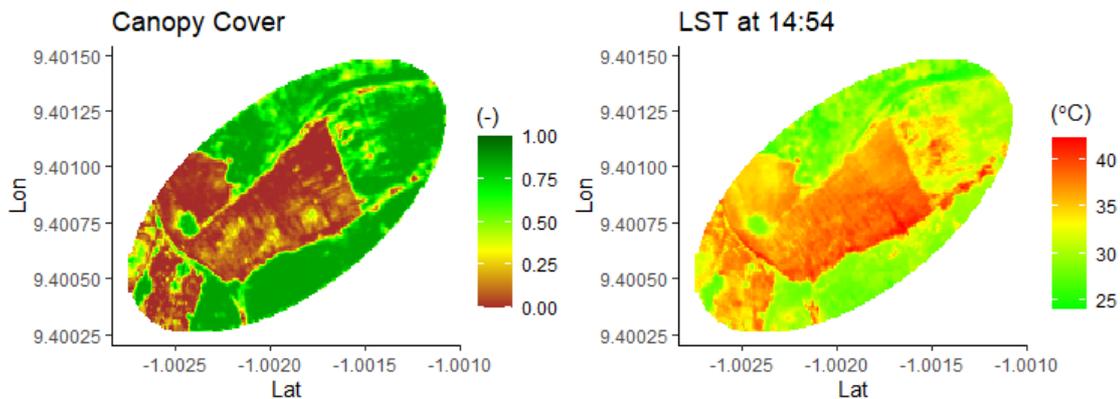


Figure 3 The canopy cover and LST measured with the drone.

The drone images are made on 27-08-2019 at four moments during the day with a DJI mavic pro. During these four moments, the surface temperatures are measured and the canopy covers are calculated. Unfortunately, we could not use the NDVI that was constructed with the drone, because of low sensitivity of the sensor. Therefore, we had to use the canopy cover results, which were easier to determine with the used sensor. The surface temperature is measured with a FLIR Duo R and the canopy cover is constructed with the measurements of the MAPIR Survey3 camera. The canopy cover map of the surface temperature has a resolution of 1m. For the canopy cover a composite is made of all the pictures taken that day. An Example of the Canopy Cover and LST measurements made by the drone are given in Figure 3. Figure 3 clearly shows that the field mainly consist out of bare soil, which results in higher temperatures compared with its surroundings.

2.2.2 In-situ measurement station



Figure 8 The TAHMO station in the measurement field.

Inside the field where the drone images are taken a continuous measurement station is located. This station is part of the Trans-African HydroMeteorological Observatory (TAHMO) (*TAHMO Website*, n.d.) and measures: pressure, radiation, relative humidity, soil moisture, soil temperature, air temperature, wind direction and windspeed. TAHMO is also a partner of the TWIGA project. The measurements start at 24-04-2019 until present day with a five-minute interval. The measurement station is shown in Figure 4.

2.2.3 Satellite images

MODIS

For constructing the triangle, the MODIS satellite is used. The MOD11A2 V6 product is used for the Land Surface Temperature (LST) at day and night. This product has a resolution of 1km and gives a 8-day average of the LST. The MOD13A2 V6 product is used for the Normalized Difference Vegetation Index (NDVI) and has also a resolution of 1km. The NDVI images give the best available value in a 16-day period. For both the products of the LST and the NDVI monthly composites are made by calculating the mean of all the images that are taken in that month. These monthly composites are made to reduce the effect of clouds. As an example, a monthly composite of the LST and the NDVI are given in Figure 5a and 5b respectively.

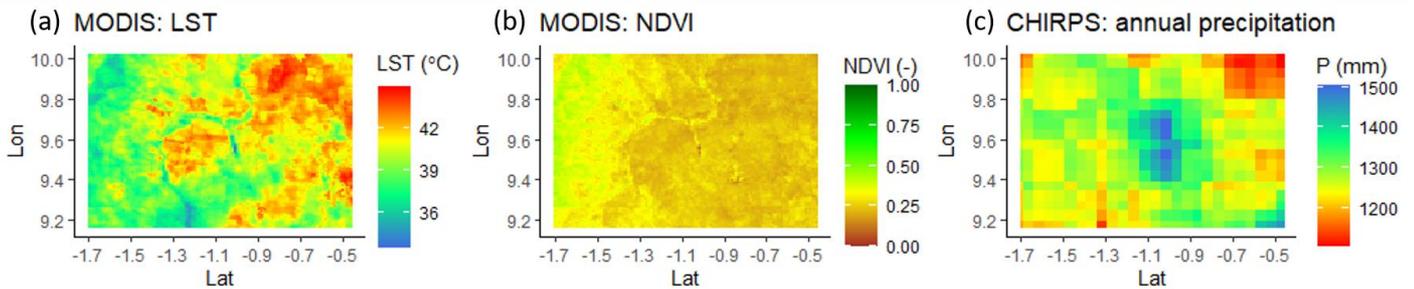


Figure 9 Examples of the LST (a) and NDVI (b) of the MODIS and the annual precipitation (c) of the CHIRPS.

CHIRPS
The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is used to select a dry, wet and normal year. This is a data set that incorporates 0.05° resolution satellite data and in-situ data of precipitation. For the years between 1998 and 2019 a yearly precipitation sum is calculated. These sums are based on the are shown in Figure 5c.

Sentinel-1

From Starlab we received soil moisture maps for April and May 2019, with a resolution of 30m. Starlab is a private Research and Development company which is specialised in the Space and Neurotechnology sectors (*Starlab Website*, n.d.). Starlab is also a partner in the TWIGA project. The soil moisture is based on Sentinel-1 data and in-situ measurements. The area for which the soil moisture is calculated is shown in Figure 6a. For both the months April and May, a composite is made by calculating the mean from all the images in these months.

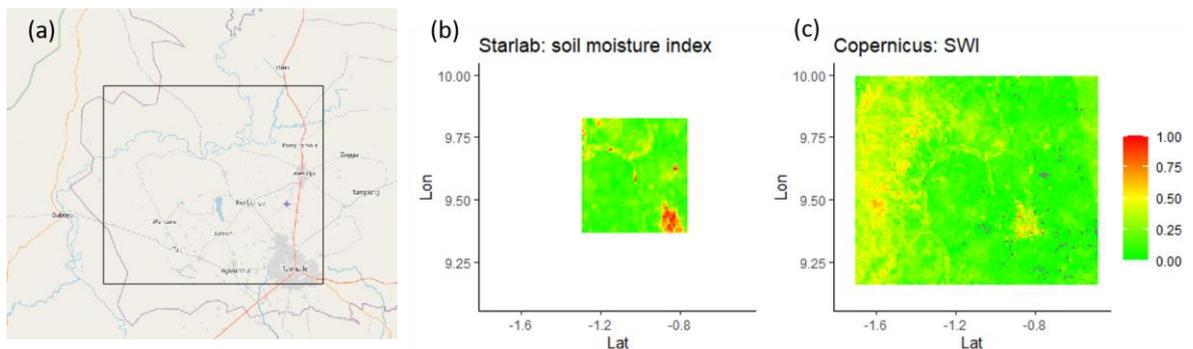


Figure 10 The study area of the Starlab data (a) with an example of the soil moisture of the Starlab data (b) and an example of the SWI of the Copernicus data (c).

Next to the Starlab data, we also used the Soil Water Index (SWI) from the Sentinel-1/Copernicus. The SWI has a resolution of 10m and is a number between 0 and 1. When the SWI is close to 1, it means

that the soil is wet and when the SWI is close to 0, it means that the soil is dry. Compared with the soil moisture product from Starlab, the SWI from Copernicus is computed in a more simplified way.

Figure 6b shows a visualisation of the Starlab soil moisture and Figure 6c the Copernicus SWI. The area of the Copernicus SWI is based on the area shown in Figure 2, but this can be adjusted to any specific area that we want. This is not the case for the Starlab data, the area shown in Figure 6a is the maximum.

Sentinel-2

From the MODIS we already have a NDVI product. However, to compare the NDVI with the canopy cover from the drone we need a product with a higher resolution. Sentinel-2 provides a NDVI product with a resolution of 20m.

2.3 Triangle method

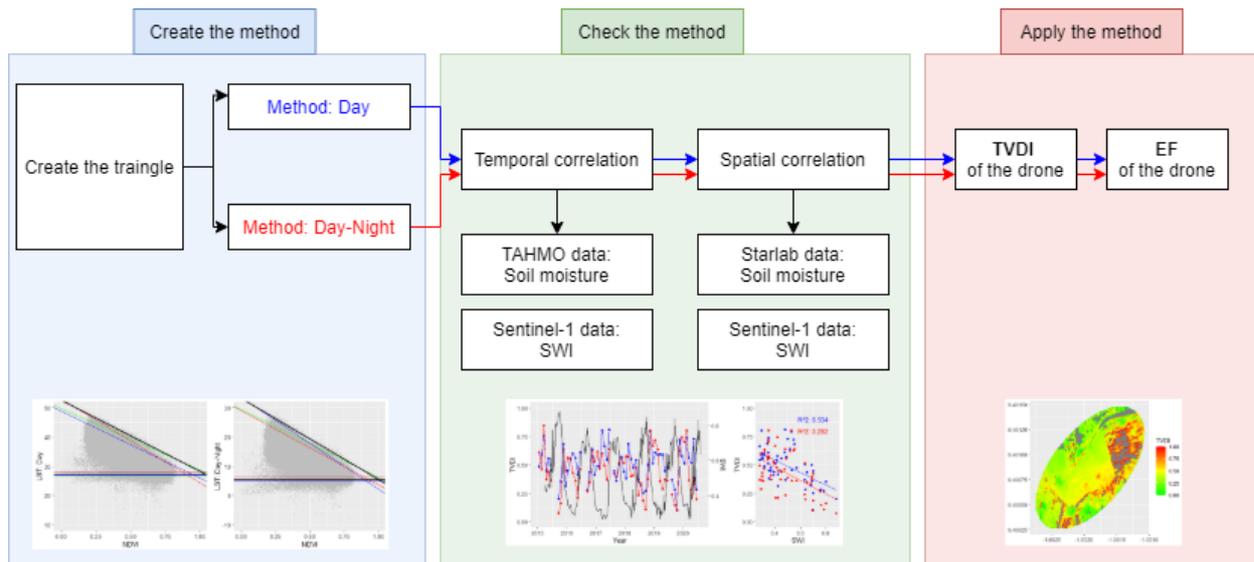


Figure 11 Overview of the method and the working process.

Throughout the following chapters the steps shown in Figure 7 will be followed. First we start by creating the method, which means creating the triangle. For the triangle method the surface temperature of every pixel inside the specific area are plotted against the corresponding NDVI, which creates a triangle shape (see Figure 1). The dry edge is determined by fitting a line through the 99,9% quantile of all the points. The wet edge is determined by fitting a horizontal line (calculating the mean) through the 5% quantile of all the points. Both these edges create then a triangle.

With these edges the Temperature Vegetation Dryness Index (TVDI) can be calculated by using the following Equation (Patel et al., 2008; Sandholt et al., 2002):

$$TVDI = \frac{T_s - T_{min}}{T_{max} - T_{min}} \quad (2)$$

$$T_{min} = \text{the wet edge} \quad (3)$$

$$T_{max} = \text{the dry edge} \quad (4)$$

Next to the traditional approach where the daily LST is used, we also use a second method. With this method the daily LST changed to the difference between the day and night LST. By calculating the difference, the effect of topography on the LST is excluded. The procedure for this method is the same as for the method where only the daily LST is used, only now the y-axis in Figure 1 changes to the difference between day and night LST. This means that from now on we have two methods from which

the TVDI is calculated; 'Method: day' and 'Method: day-night'. These two methods are also indicated in Figure 7. All the procedures that come next, will be carried out for both these methods.

We attempt to make a universal triangle, that can be applied throughout the year. This universal triangle is constructed by combining the triangles of a dry, wet and average year based on the precipitation. This is done to make sure we include all the different conditions of vegetation and soil moisture. From the combined triangle, the edges are our final dry and wet edge that will be used to calculate the TVDI. This will be done for both the methods which means we get two final dry edges and two final wet edges.

We continue with the next step, checking the method (see Figure 7). With the triangle created, the TVDI can be calculated. We begin by calculating the TVDI for the area indicated in Figure 2, using the MODIS data. To make sure that the dryness index product of the drone is correct, the TVDI of the satellite image will be checked. First, we check the TVDI based on temporal correlation and then on spatial correlation. With respect to the temporal correlation, the TVDI will be compared with the in-situ TAHMO station and the SWI of the Copernicus data. For the spatial correlation, the TVDI will be compared with both the Sentinel-1 products: the Starlab soil moisture and again the Copernicus SWI. When it seems that the TVDI of the satellite image performs well in time and space, it can be applied on the drone images.

We then arrive at our final step, applying the method (see Figure 7). First the TVDI for the drone image will be calculated, which is done by using the same triangle as before. However, for calculating the TVDI the pixels of the drone are now used. This which means the edges stay the same and Equation 2 is used again, but the location relative to the two edges is now determined by the pixels of the drone. The outcomes of the drone TVDI can again be checked by the Copernicus SWI.

After the TVDI, the Evaporative Fraction (EF) will be calculated for the drone. The Evapotranspiration (ET) is calculated based on the Priestly Taylor method (Garcia et al., 2014):

$$ET = \alpha * \frac{\Delta}{\Delta + \gamma} (1 - TVDI)(R_n - G) \quad (5)$$

Here the α is the Priestly Taylor constant and is taken as 1.5. The α is dependent on the type of landscape and how high the advection can be. If the advection is potentially very high, it means there is a lot of wind and the ET becomes higher. Therefore, the α will be higher and above 1. Normally it is assumed that for dry conditions the advection is high, together with the table in Flint & Childs. (1991), the α becomes 1.5. The Δ is the slope of the saturated vapor pressure [kPa K⁻¹] and is a function of air temperature. For this air temperature we use the temperature that is measured with the drone to add the spatial variability. The γ is the psychrometric constant [kPa K⁻¹] and is a function of air pressure. For the air pressure the data is used of the TAHMO station. Unfortunately, we do not have the data of the spatial variability of the R_n (net radiation [W m⁻²]) and the G (the soil heat flux [W m⁻²]), therefore we cannot calculate the ET. However, combining Equation 5 and 1 we get:

$$EF = \frac{ET}{R_n - G} = \alpha * \frac{\Delta}{\Delta + \gamma} (1 - TVDI) \quad (6)$$

With this formula we can calculate our final product: the EF for the drone image, which gives indication of the variability of the ET on field scale based on a relatively simple remote sensing product.

3 Results and discussion

3.1 Determine the years

First, three years are selected, which include a dry, wet and average year and are used to build the triangle. These years are based on the yearly precipitation sum and calculated from the average of the CHIRPS data. Figure 8 shows these yearly precipitation sums from 1998 until 2019. The red line indicates the mean and the blue lines indicate the 10th and 90th percentile.

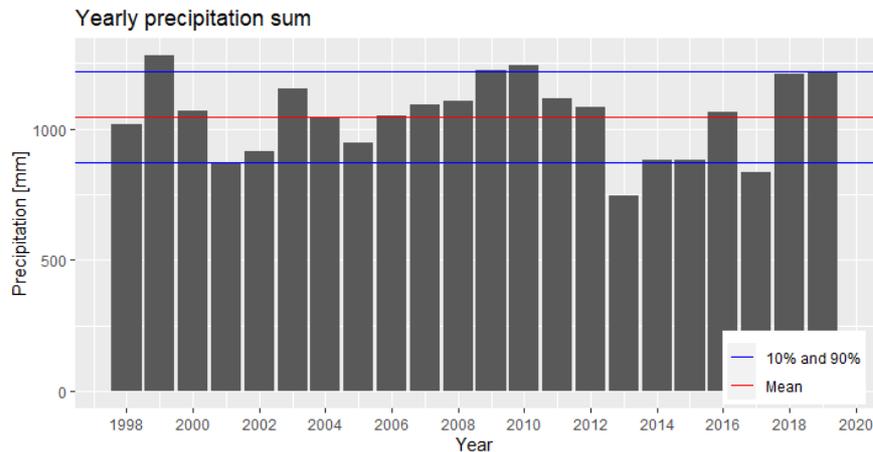


Figure 12 The yearly precipitation sum for the years 1998 until 2020.

Figure 8 indicates that the years 2000, 2004, 2006 and 2016 are the closest to the red mean line. We choose to use the data of the year 2006 to represent the 'normal' year. We selected this year because compared with the other years, the precipitation sum of the previous and the next year are no extremes.

For the year that represents the dry year, we need to look at the lower blue line, which represents the lowest 10%. The years 2013 and 2017 have a precipitation sum that lies beneath this line. To exclude potential outliers and errors, we choose to use the year 2017 to represent the dry year and not the most extremes year of 2013.

For the representation of the wet year, we look at the upper blue line. Here, the years 1999 and 2010 exceed this line. With the same reasoning as for the dry year, were we want to exclude the outliers and potential errors, we choose to use the year 2010 to represent the wet year.

This means that the years: 2006, 2010 and 2017 are used to build the triangle were the TVDI will be calculated with.

3.2 The universal triangle

The NDVI and the Land Surface Temperature (LST) of the MODIS data for the years 2006, 2010 and 2017, inside the area shown in Figure 2, are used to create the triangle. All these points are plotted against each other and shown in Figure 9. Through the 99,9th percentile of all these points the dry edge is fitted and through the 5th percentile the wet edge is fitted. These edges are fitted for each year separately and for all the points combined. Figure 9 shows the two methods were the day LST is used and the difference between the day and night LST. The edges for each separate year are indicated with a colour and the final edges are indicated with black.

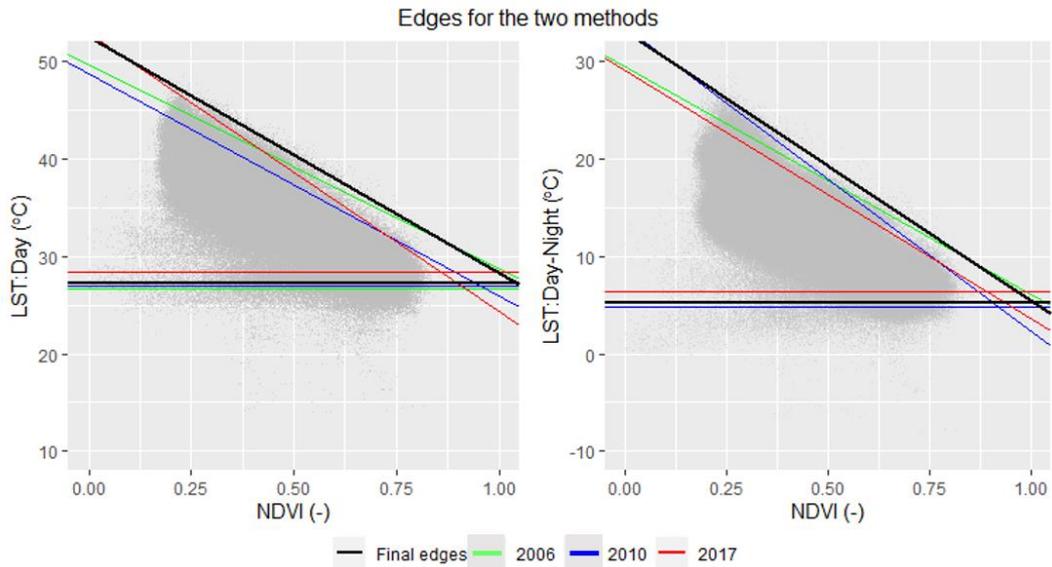


Figure 13 The resulting two triangles based on the method with LST day and the difference between day and night LST.

Figure 9 shows minimal difference between the edges of the different years, especially for the wet edges. All the edges are very close to each other and the slopes hardly vary. To calculate the final edges, we combined all the years.

The final edges are based on all the points from every year, where we focus on the outer points. Figure 9 shows that for both the methods the points create more clear edges for the dry edge compared with the wet edge. The wet edge has more outliers compared with the dry edge. Therefore different percentiles were used to determine the edges. For the wet edges more points are considered where the edge is fitted through compared with the dry edge. This can clearly be seen in Figure 9, where the dry edge follows the outer edge of the triangle and the wet edge ignores some points at the outer edge.

The final edges for both the methods form a very clear triangle. Both the edges cross around 1 NDVI, which would be expected from the triangle method. Figure 9 indicates no clear differences between the two methods. Both the triangles have around the same slope for the dry edge and the same range for the y-axis. With these final edges the dryness index can be calculated.

3.3 Validation the dryness index

With the help of the edges in Figure 9 and Equation 2, the Temperature vegetation dryness index (TVDI) can be calculated. We have done this with satellite data of MODIS and the drone image. To check how well this TVDI is performing, the temporal and spatial correlation is evaluated of the TVDI resulting from the MODIS.

Figure 10 shows some examples of the TVDI calculated with the MODIS data for the area in Figure 2. In Figure 10, the months February and September of 2019 are shown. February is a dry month and September is a wet month, which can clearly be seen in Figure 10. February has higher values for the TVDI compared with September. This is already a first indication that the method performs well. Another quick indication that demonstrates that the method performs well, is the visibility of the river. In both the Figures the river is clearly flowing through the middle of the picture. A river consists out of water and is therefore colder compared with its surroundings, which is demonstrated by both the months in Figure 10.

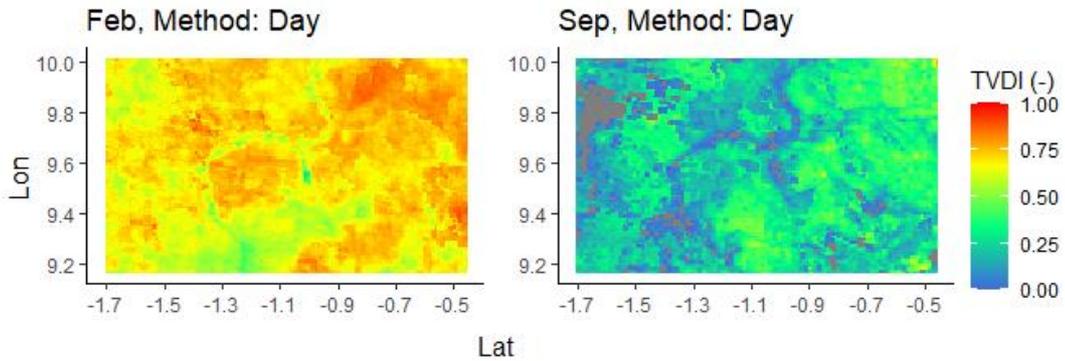


Figure 14 Example of the TVDI for February and September, only for the method with the day LST.

To determine how accurate the triangle method is for calculating a dryness index, we carried out some temporal and spatial analysis with the TVDI maps from Figure 10.

3.3.1 Temporal correlation with satellite data

The accuracy of the TVDI, based on the temporal correlation, is carried out for 1 specific point. This point is the pixel which is located as close as possible to the TAHMO station. First the temporal evolution of the TVDI at this specific point is compared with the TAHMO station. Second this point is compared with the Copernicus SWI. The comparison between the soil moisture of the TAHMO station and the TVDI is shown in Figure 11.

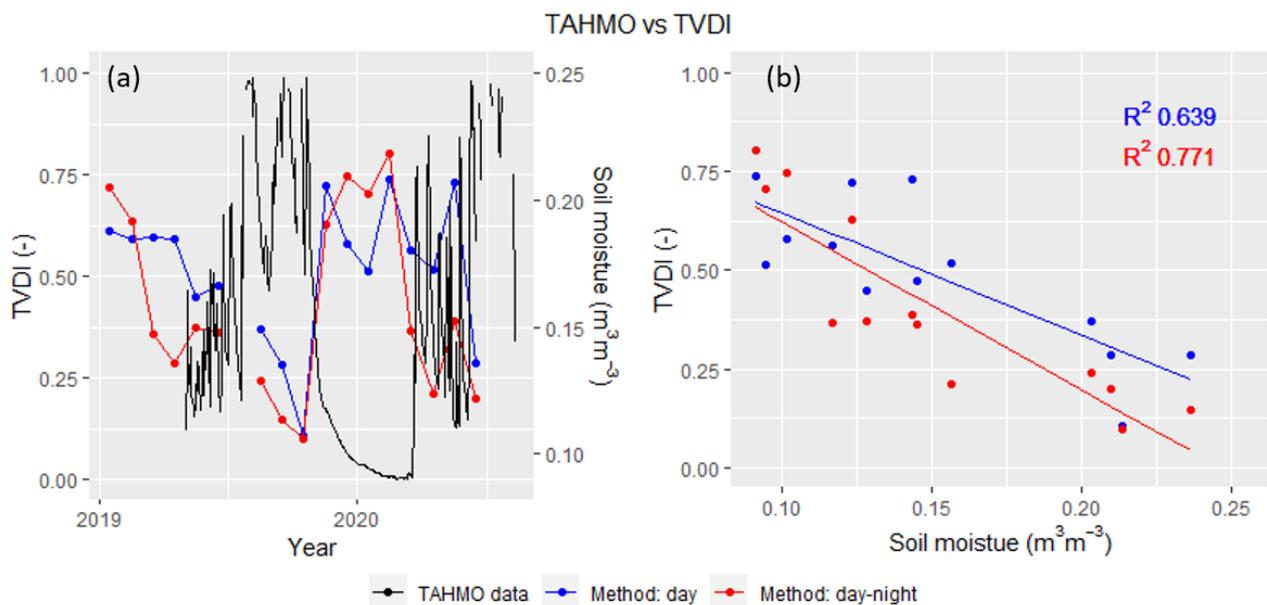


Figure 15 The comparison between the TVDI and the soil moisture of the TAHMO station for the years 2019-2020 (a) and the statistical analysis (b) at the TAHMO location.

Figure 11a shows the temporal evolution of the TVDI for both the methods and the measured soil moisture of the TAHMO station. Here it becomes clear that the TAHMO data is more variable compared with the TVDI. This happens because the TAHMO data is daily measured and the TVDI is from a monthly composite. Figure 11a clearly indicates that the relation between the TVDI and the soil moisture is negative. When the TVDI decreases, the soil moisture increases and the other way around. Especially around 1 September 2019, where the soil moisture has a sharp decrease, the TVDI also increases rapidly. During the time frame in Figure 11a, no clear difference can be seen between the two different methods.

To compare the TVDI with the measured soil moisture of the TAHMO station statistically, the monthly average of the soil moisture is calculated. Figure 11b shows the comparison between the monthly average of the soil moisture and the TVDI based on the two methods. Through these points a linear regression model is fitted and the R^2 is determined. Here we see again that the TVDI and the soil moisture have a significant negative relation. Compared with Figure 11a, now a difference between the two methods is shown. The method where the difference between the day and night LST is used to calculate the TVDI, gives a more negative relation with the TAHMO soil moisture and has a higher R^2 compared with the method where only the day LST is used.

Compared to other studies, the R^2 shown in Figure 11b are relative high. Du et al. (2017) used the method where the difference between day and night LST is applied to calculate the TVDI. They then compared it with the soil moisture and another dryness index product. The resulting R^2 were 0.213 and 0.47 respectively. Sandholt et al. (2002) used the method where only the day LST was used and compared the TVDI of different locations with the soil moisture. The R^2 varied between 0.5 and 0.7. Patel et al. (2008) used also the method where only the LST was used. They compared again the TVDI with the soil moisture, but also looked at different months. Here the R^2 varied between 0.62 and 0.33. From these studies it becomes clear that the performance of the TVDI depends on location, the specific time it was calculated and which product it is compared with. Looking at the results of these studies it can be concluded that the resulting R^2 of Figure 11b are high, but different time scales, locations and comparison products should also be considered. Therefore, we first look at a longer time period, combined with another comparison product.

Figure 11 only shows the performance of the TVDI for a period of one year. The TVDI depends on the type of year and it is therefore important to look at the performance of the TVDI for several years. We did this by comparing the TVDI with the soil water index (SWI) of the Copernicus data. The results of this comparison are shown in Figure 12.

Figure 12a shows again the temporal evolution of the TVDI of both the methods but it is now compared with the Soil Water Index (SWI) from the Copernicus data. Again, we see that when the SWI decreases, the TVDI increases and the other way around. This effect is especially clear between the years 2018-2020. The TVDI around the year 2017 performs less good. Here we see that the TVDI does not go down when the SWI goes up. This could be related to the dryness of year 2017. Figure 8 already indicated that year 2017 was a dry year, which could have influenced the performance of the TVDI. When the two different methods are compared, again no clear difference can be seen. They both perform well between the years 2018-2020 and perform less good around 2017.

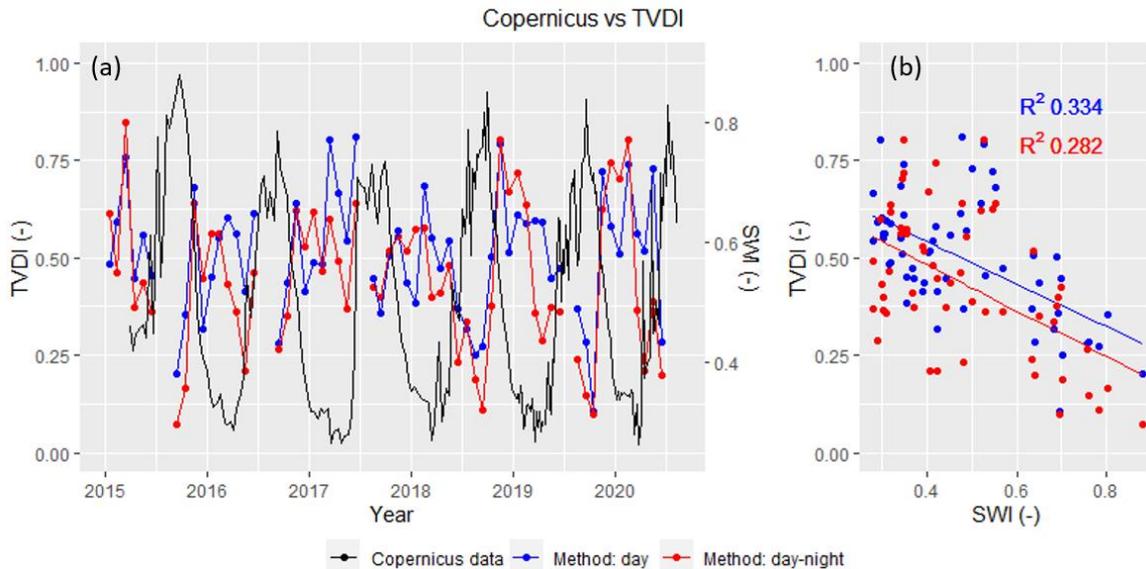


Figure 16 The comparison between the TVDI and the SWI of the Copernicus data for the years 2015-2020 (a) and their statistical analysis (b) at the TAHMO location.

Figure 12b presents how well the TVDI and the Copernicus SWI correlate. The R^2 of the linear regression for both the methods are lower compared with Figure 11b, where the TVDI is compared with the TAHMO data. Comparing Figure 11b with Figure 12b, the method where the difference between day and night LST is used gives again a steeper relationship between the TVDI and the SWI. This results in lower minimums for the TVDI, see Figure 12a. However, now the method where only the day LST is used performs better than the Method where the difference between day and night LST is used. Comparing the R^2 between the Figures 11b and 12b we see that now the TVDI performs less well. Both the R^2 are now relatively low when they are compared with the studies from Du et al. (2017); Patel et al. (2008); Sandholt et al. (2002). This decrease in performance could be linked to the year 2017.

We have tried to improve the results from Figure 12, by doing a sensitivity study for the percentiles of the edges and see if the R^2 improves. With increasing and decreasing the percentiles that are used to calculate the edges, new R^2 are calculated and shown in Table 1 in Annex 1. Table 1 Indicates clearly that the R^2 hardly improves by changing the percentiles, therefore we use only the 5th percentile for the wet edge and the 99.9th percentile for the dry edge.

Here it could be concluded that it depends on the time resolution how well the TVDI performs and which method should be used to calculate the TVDI.

When looking at other studies (Garcia et al., 2014; Sandholt et al., 2002), it can be concluded that the performance of the TVDI depends on the location. The TAHMO station is located in a diverse landscape, with houses, roads, fields and savanna. This makes it difficult to calculate one specific TVDI for this landscape. Therefore we also looked at other landscapes and the spatial correlation of the TVDI.

3.3.2 Spatial correlation with satellite data

We have already seen in Chapter 3.3.1 that it depends on the time resolution how well the TVDI performs. Now we are going to evaluate the dependence of the TVDI performance on the location. Previously the analysis was focused on the location of the TAHMO station. As already mentioned, this location has a diverse landscape. To reduce the effect of the diversity of the landscape on the TVDI we looked at two other locations; Location 2 (9°54'14.4"N 0°32'02.4"W) which is located in the most northern part with mostly agricultural fields and Location 3 (9°51'32.4"N 1°07'37.2"W), which is located close to the river

with a savanna as the dominant landscape. An indication of the location of these points is given in Figure 21 in Annex 2. For these two locations, the TVDI is again determined and compared with the Copernicus SWI. These results are shown in Figure 13.

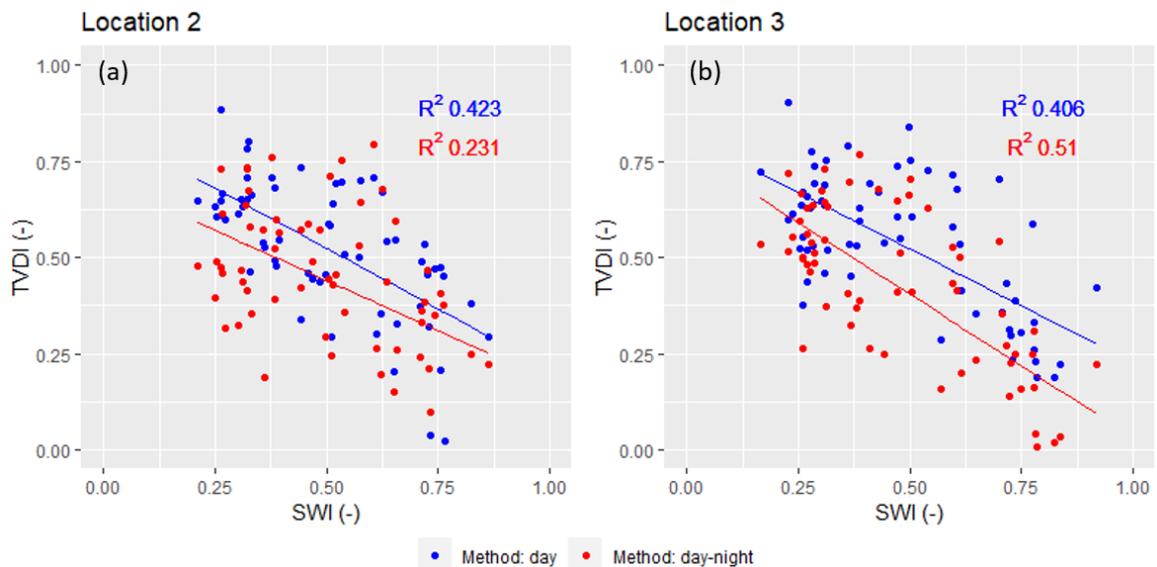


Figure 17 Statistical analysis between the TVDI and the SWI of the Copernicus data for location 2 (a) and location 3 (b) for the years 2015-2020.

Figure 13a shows the results of location 2. Compared with the TAHMO station location, location 2 improves for the method where only the day LST is used. This improvement can be related to the behaviour of the TVDI around 2017, see Figure 22 in Annex 2. Now we see that also around 2017 the TVDI decreases and increases when the SWI increases and decreases. At this location, the method where only the day LST is used, becomes the best method.

At location 3, the method where the difference between the day and night LST is used, becomes now the best method, see Figure 13b. At location 3, both the methods improve compared to the TAHMO station location. Again, this improvement can be explained by the year 2017, see Figure 22 in Annex 2. To calculate the SWI from the Copernicus data and the TVDI from the MODIS data it is best to have a homogeneous landscape that does not change much throughout the years. Agricultural fields change throughout the year, because fields must be worked and crops have to be sowed and harvested. Therefore the savanna landscape (Location 3) gives the best results, compared with the agricultural fields (Location 2) and the combined landscape (TAHMO station).

Compared with the studies Du et al. (2017); Patel et al. (2008); Sandholt et al. (2002), we see again that the performance of the TVDI highly depends on the location. The R^2 from location 3 becomes relatively high compared with the other studies, which means that the TVDI also performs well when it is compared with the Copernicus SWI. However, this is location specific.

Here we can conclude that it is very important to determine what the landscape and vegetation looks like where the TVDI is calculated. This has a great influence on how well the TVDI performs.

Next to looking at the performance of separate locations, we also looked at the performance of all the pixels from a large area. Here we calculated the TVDI for the complete area of Figure 2 and Figure 6a and compared it with the SWI of the Copernicus data and the soil moisture of Starlab respectively. However, we are comparing different dryness indicators with our TVDI. This is done because all these

indicators behave a bit differently and it is not for sure to say which one is the most accurate. Therefore we will now compare first the data from Copernicus with the data from Starlab. These products have some differences; the Copernicus method for calculating the SWI is simplified compared with the method to calculate the soil moisture from Starlab. Next to that, the Starlab data has a higher resolution compared with the Copernicus data. The Starlab also uses the TAHMO station to calibrate their product, but the SWI of the Copernicus data is only based on the signal of the satellite.

For this analysis, the months April and May are chosen for the year 2019, the area of the SWI is made smaller and the resolution of the Copernicus data is downscaled. The resulting pixel are then compared and shown in Figure 14.

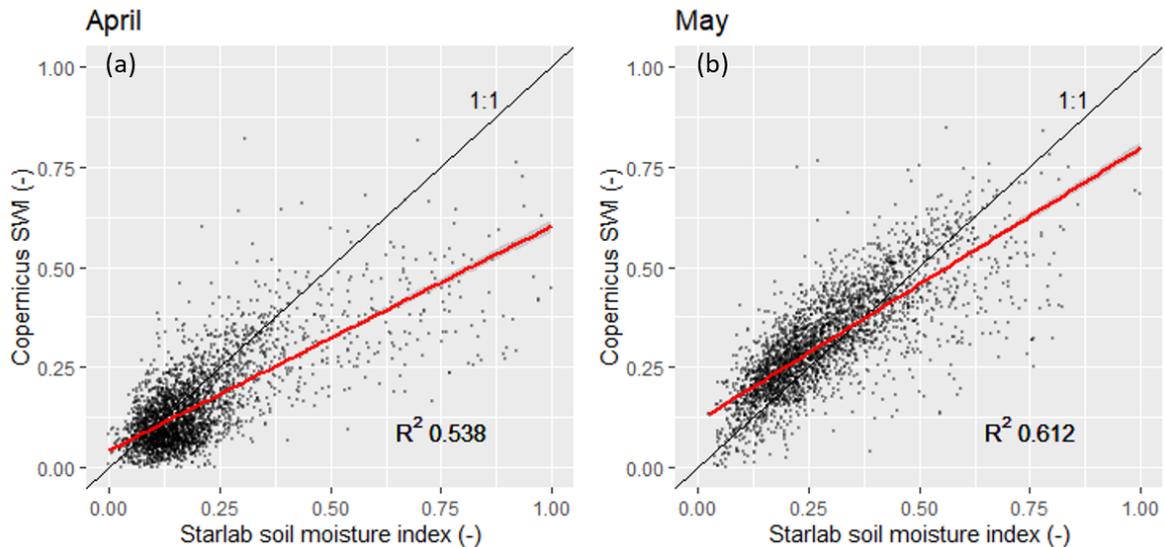


Figure 18 Statistical analysis between the Copernicus SWI and the Starlab soil moisture index, for April (a) and May (b). This analysis is based on the complete area.

Figure 14a shows the results for April and Figure 14b shows the results for May. The black line indicates the 1:1 line. For both the months, the points follow this line, especially for the lower values. When the values become higher, the points deviate from this 1:1 line. However, this effect is less visible in the month May, which could be related to the increasing wetness during this month. May is wetter compared with April and already longer in the raining season. This means that the soil moisture and the SWI are more divided between the lower and the higher values, which reduces the outliers. The reduction of the outliers also causes the R^2 to go up in the month May.

Despite this difference, both months show a significant relationship between the SWI of the Copernicus data and the soil moisture of the Starlab data and a relatively high R^2 . It is very hard to say which method gives the best results, and which method we should use to compare our TVDI with. However, we can say that both methods produce similar soil moisture values.

With the comparison between the Copernicus SWI and the Starlab soil moisture, we can compare our TVDI with these two products. This is done by plotting all the resulting pixels from their areas against each other for the two months, April and May. The results are shown in Figure 15 In Figure 15 the (+) indicates if the relationship is significant and the black line indicates the linear regression line. First, we focus on the comparison between the SWI and the TVDI, which are the Figure 15 a,b,c and d.

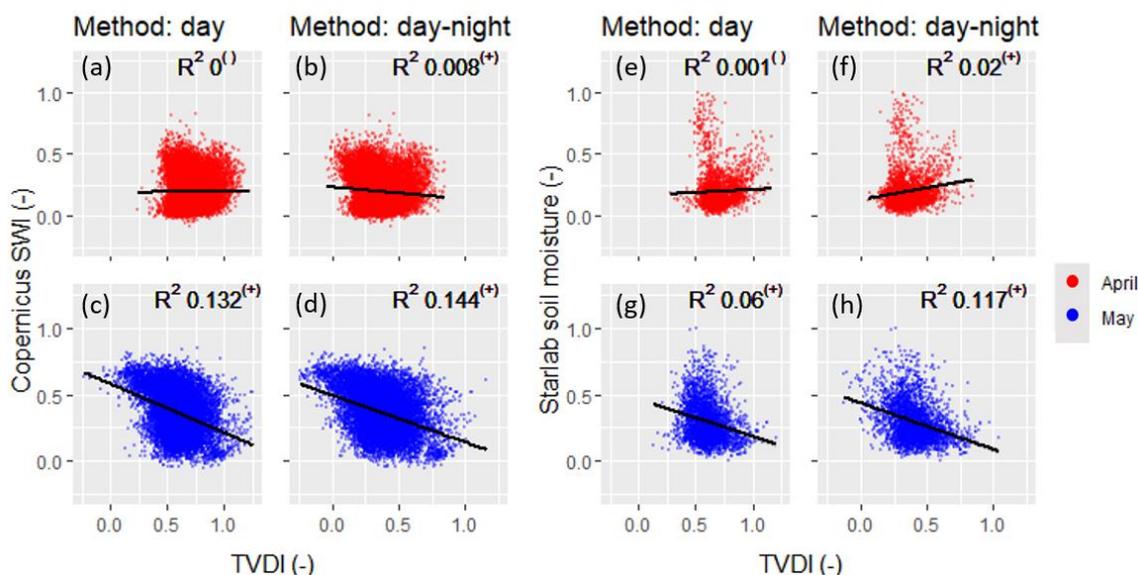


Figure 19 Statistical analysis between the Copernicus SWI and the TVDI, for April and the day method (a), for April and the day-night method (b), for May and the day method (c), for May and the day - night method (d) and the Statistical analysis between the Starlab soil moisture and the TVDI, for April and the day method (e), for April and the day-night method (f), for May and the day method (g), for May and the day-night method (h). This analysis is based on the complete area.

Looking at the indication of the significance, a clear difference can be seen between the two months (Figure 15 a and b vs c and d). The relationship between the TVDI and the SWI is always significant in May but not always in April. The pattern that the month May performs better compared with April is also observed with the R². The R² is higher in May compared with April. We think that the month May is performing better because this month is wetter (see Figure 14). The SWI of the Copernicus data is based on the soil moisture. The TVDI is based on the LST and the NDVI. This means that plants play an important role in determining the TVDI but not as an important role for the SWI. It takes a bit of time before plants react to soil moisture. Therefore the TVDI may experience a lag compared to the SWI. In the month May the soil is already made wetter for a longer period compared with April, and the plants have had the time to catch up. Therefore the month May performs better. However, the R² in May is still very low compared to the other studies (Du et al., 2017; Patel et al., 2008; Sandholt et al., 2002).

When looking at the difference between the methods (Figure 15 a and c vs b and d), we see very little difference. The method where the difference is used has a higher R² compared with the method where only the day LST is used. However, this difference is very minimal and the improvement still gives a very low R².

Now we focus on the comparison between the soil moisture of Starlab and the TVDI, which are Figure 15 e, f, g, h. Here the same patterns occur as for the relationship between the SWI and the TVDI. The month May again improves with the significance and the R² compared with April, the R² is still very low and there is no clear difference between the two methods. We already concluded with Figure 14 that the two products are fairly similar, which we see again here.

Here we can conclude that it again depends on the time of year how well the TVDI performs. However, it is better to look at more than one specific point to determine the performance of the TVDI. We already saw with Figure 12 and 13 that it depends on the location how well the TVDI performs and in Figure 15 all these points are put together. Then it can be expected that the R² decreases. When we do not look at Figure 15, but only at the analysis based on a specific point, we know that the TVDI performs well.

Here we have to take into account that the TVDI is sensitive for the time resolution and location. Therefore we can now continue with our analysis of the drone.

3.4 Application for the drone

Before applying the TVDI on the drone images, we are going to check the measurements of the drone. The drone measured the LST and the canopy cover. First the LST is evaluated. We do this by comparing the LST measurements of the drone with the temperature of the TAHMO station. The TAHMO station does not measure the LST, but it measures the temperature 9cm below the ground and 2m above the ground. To stay as close as possible to the LST, we use the temperature 9cm below the surface for comparison with the LST of the drone. The LST from the drone at the exact location of the TAHMO station, is subtracted. There are four drone measurements made, which means we have four LST points for comparison with the TAHMO temperature. This result is shown in Figure 16.

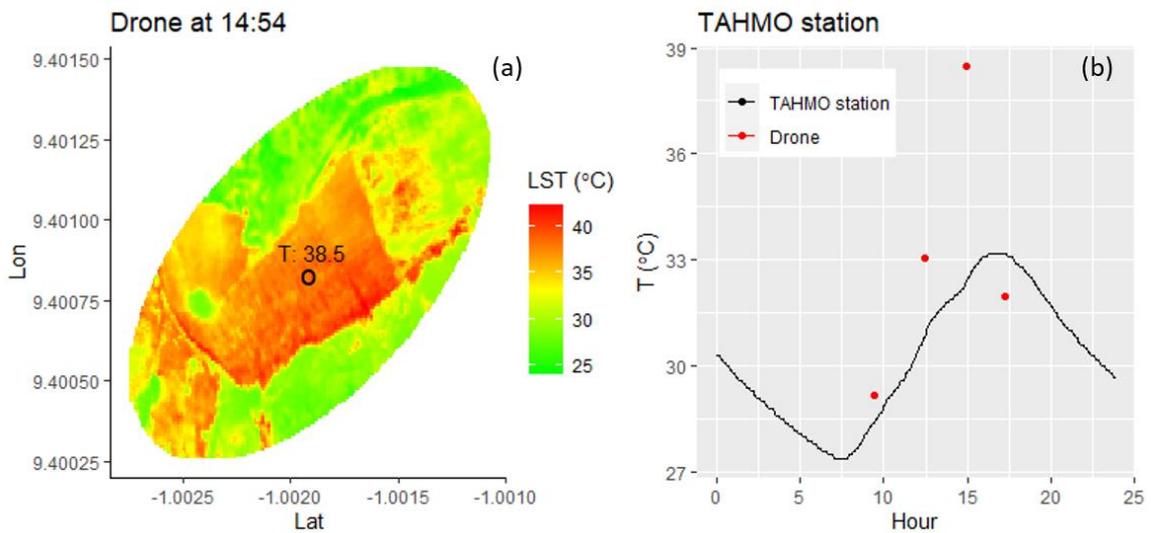


Figure 20 The LST measured by the drone at 14:54 (a) and the comparison between the TAHMO ground temperature and the drone LST (b).

Figure 16a shows the LST of the drone. The circle indicates the location of the TAHMO station, where the 38.5 indicates the temperature measured with the drone at this location. A clear distinction can be seen between the agricultural field and the vegetation located next to it. In Figure 4 we could see that the agricultural field consisted mainly out of bare soil and some low crops. The vegetation next to the field consisted of large vegetation and little bare soil. This difference in vegetation causes the large temperature difference. The large vegetation cools the surface and the bare soil cannot do that, which results in a very hot agricultural field compared with its surroundings. With the high LST we can very easily indicate the location of the field.

Figure 16b shows the comparison between the LST from the drone images and the temperature measured with the TAHMO station. The point at 14:54 Hour of 38.5 degrees is also indicated in Figure 16a. Here we can see that the comparison between the LST of the drone and the soil temperature of the TAHMO station is not very good. Most of the points are close to the line of the TAHMO data, only the point at 14:54 highly overestimates the TAHMO data. This could be caused by the difference in heights where the temperature is measured. The LST is measured very close to the surface, which will result in the highest temperature during the day and the lowest temperature during the night compared with other heights. When you go further into the ground this effect is dampened, the peaks during the day and night will be less high and low. Therefore, it becomes difficult to compare these two values. To get still a first insight on how well the LST of the drone performs, we see that the points at 9:26, 12:28, 17:15 Hours

are relatively close to the TAHMO measurements. The drone temperature at 14:54 differs a lot with the TAHMO temperature, but this pattern is also what you would expect. The LST peaks higher compared with the temperature beneath the ground. Therefore we can conclude that with this first indication, the LST of the drone performs relatively well.

Second the canopy cover of the drone will be evaluated. As we already explained, we tried to measure the NDVI with the drone, but this was not successful. Therefore we use the canopy cover. To check the measurements of the canopy cover of the drone we compared these measurements with the Sentinel-2 NDVI. The NDVI of the Sentinel-2 has a resolution of 20m and is better equipped for comparison with the drone images compared than the 1km resolution MODIS NDVI. The canopy cover measurements of the drone have resolution of 1m. For comparison with the NDVI the resolution of the drone measurements needs to decrease to 10m. Another adjustment that needs to be made to the canopy cover is adjusting the maximum value. The canopy cover measurements can reach 1 or even above 1. This is not possible for the NDVI. Therefore we scaled the canopy cover by multiplying the canopy cover with the maximum value of the NDVI measurements. The resulting maps of the canopy cover of the drone and the NDVI of Sentinel-2 are shown in Figure 17.

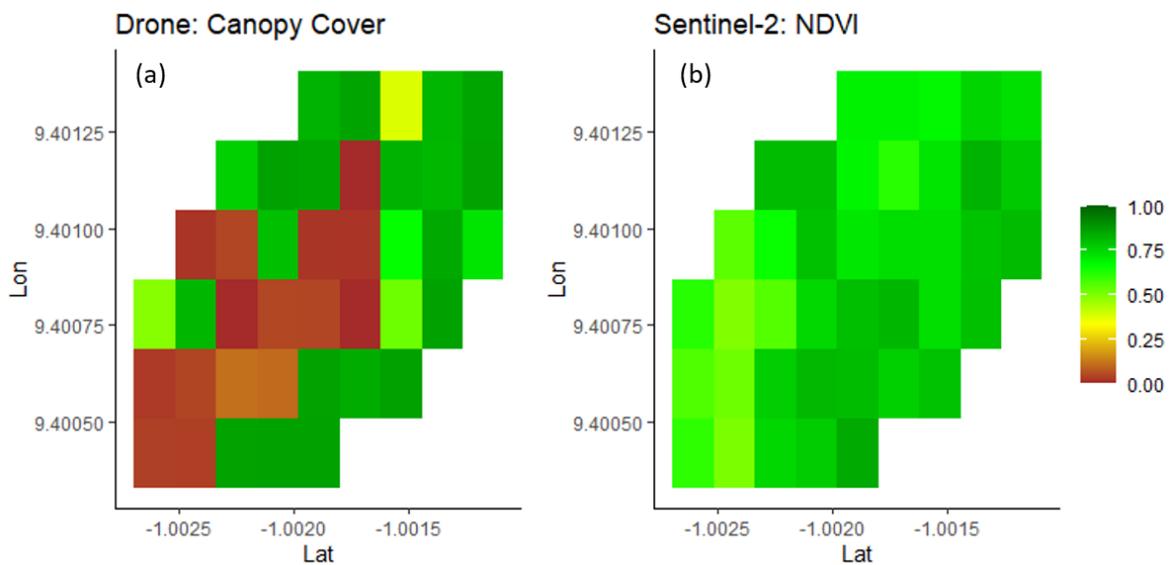


Figure 21 The canopy cover measured by the drone (a) and the NDVI measured with the Sentinel-2 (b).

Figure 17a shows the results of the canopy cover of the drone. Here we see that in the middle of the map the canopy cover is low compared with the rest of the map. This is the agricultural field, which consists mainly out of bare soil. The surroundings consist out of a lot of vegetation and this can also be seen in Figure 17a. This pattern of, in the middle of the map a very low canopy cover and the surroundings a high canopy cover, cannot be seen in Figure 17b. The NDVI does not show this pattern. There are some possibilities that could cause this difference. First, the canopy cover had to be downscaled, which resulted in a loss of detail. Second, the Sentinel-2 image is not from the exact day as the drone images and last the canopy cover is not the same as the NDVI. The measurement errors with the NDVI of the drone could also have caused some problems with the canopy cover from the drone. All these differences could cause the difference in spatial pattern between the drone and the Sentinel-2 data. This can have some consequences when calculating the TVDI.

The LST and the canopy cover of the drone, with a resolution of 1m, are now plotted inside the triangle from Figure 9. With the points inside the triangle, the TVDI can be calculated for the drone with the same edges as Figure 9. The resulting TVDI for the drone and the pixels from the drone in the triangle are shown in Figure 18.

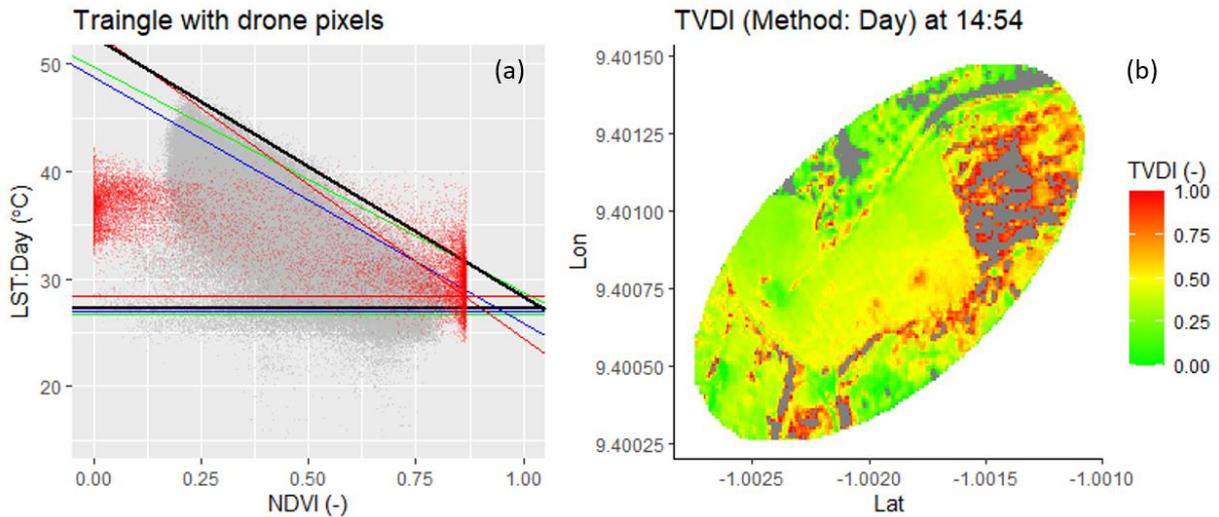


Figure 22 The drone pixels included in the triangle (a) and the resulting TVDI for the drone (b).

As Figure 18a indicates, we only used the day method. We do not have drone measurements from during the night and therefore we cannot apply the method where the difference between day and night LST is used. The red points in Figure 18a indicate the pixels of the drone, where the canopy cover is plotted against the LST. Here we see that not all the points fall into the triangle (the black lines). The points that fall outside the triangle would give a very high or negative TVDI, which would be very strange and is technically not possible. Therefore we will ignore those points. That so many points are located outside the triangle could be related to the canopy cover, which we use instead of the NDVI. Another reason is that this triangle is based on LST and NDVI with a resolution of 1km. The drone has a resolution of 1m. With a higher resolution you could miss a lot of details and ignore the higher and lower temperatures that are located inside these details.

With the points inside the triangle of Figure 18a the TVDI is calculated for the drone and the results are shown in Figure 18b. The grey area indicates the pixels who fall outside the triangle. One important statement needs to be made here. The data that is used to create the triangle is measured roughly around 11:00 AM. The most reasonable choice would be, to use the drone data from 12:28 to calculate the TVDI. However, when we tried to do this, most of the points did not fit into the triangle. This can be explained by how the triangle is calculated. For the triangle we use an average per month and a lower resolution compared with the drone. This means that you lose a lot of detail and the peaks. With the drone you can measure a lot of these details and the higher and lower peaks. For example, the surroundings outside the agricultural field have a very high canopy cover but are still very cool at 12:28. These types of details are not captured with the satellite and are therefore not included into the triangle. Therefore, there is a mismatch when the triangle that is used for the drone. To make sure we can make a TVDI picture of the drone image, we must look at a later point of the day (a very hot point). Then the high canopy cover places can fit into the triangle, but when you take a picture later it becomes a bit unrepresentative with the actual dryness. You cannot compare this picture of the drone with the larger area in Figure 10, but we can look at the relative difference inside the drone image.

There is some difference noticeable inside the agricultural field. The TVDI at the northern part of the field is lower compared with the south side. This means that it is drier at the south side and this side needs

more water. Here we can conclude that we can only look at the relative difference inside the drone image to determine the spatial difference of the dryness index inside an agricultural field.

To check these outcomes of the drone, we compared the TVDI of the drone again against the SWI of the Copernicus data. However, we used now the 10m resolution of the Copernicus data and decreased the resolution of the drone. The comparison between these two products is shown in Figure 19.

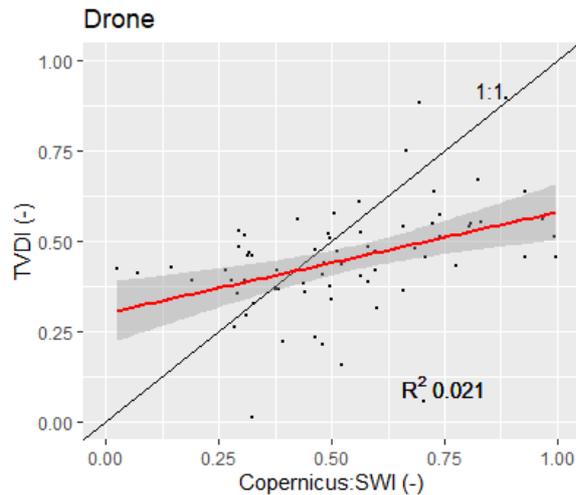


Figure 23 The statistical analysis between the TVDI and the SWI of the Copernicus data at 14:54 for the complete drone area.

Figure 19 shows the comparison between the TVDI and the Copernicus SWI with the black dots. The red line indicates the linear regression and the black line is the 1:1 line. As the Figure shows, the results are very noisy and the correlation is positive. This results in no significance of the relationship between the TVDI and the SWI and a very low R^2 , which means that the TVDI correlates poorly with the SWI and could therefore have some faults.

There could also be other reasons why this relationship is this bad. We already compared the Copernicus with our TVDI in Figure 12 and 13 and there it worked better. In Figure 12 and 13, the SWI had a resolution of 1km, but now it has a resolution of 10m. The Copernicus SWI is noisy at this high resolution and therefore it could give fewer good results compared with the lower, 1km, resolution. Another problem is the decreased resolution of the drone. We already saw with the canopy cover (Figure 17), that decreasing the resolution results in losing the details. Decreasing the resolution of the drone could result in less good results. However, we must keep in mind that the method to calculate the TVDI has some flaws. How well it works depends on the location, time and resolution. To make sure how well the TVDI works for the drones, we need more validation data.

We still think that the TVDI is a good method, when you have very little data and need a simple method to calculate the spatial pattern of the dryness index. For the resulting TVDI it must be kept in mind that this method has some flaws and the numbers should be taken relative in comparison with its own picture. Despite the comparison between the SWI and the TVDI, we continue to calculate the Evaporative Fraction for the drone. The EF is calculated with the TVDI of Figure 18b, the temperature of Figure 16a and Equation 6. The resulting EF is shown in Figure 20.

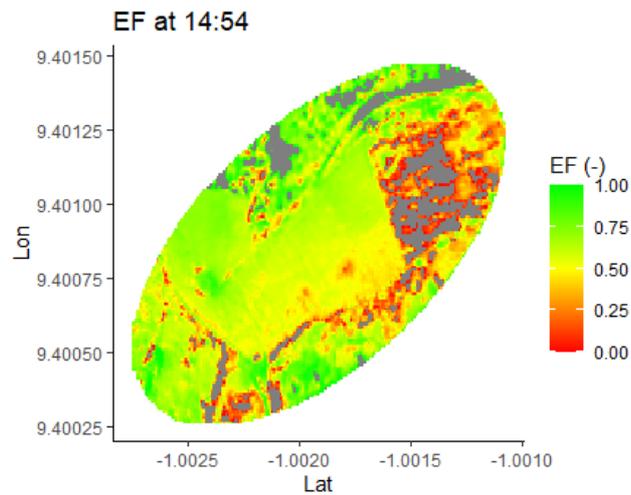


Figure 24 The resulting Evaporative Fraction (EF) for the drone area at 14:54.

Figure 20 shows the EF at 14:54. The grey areas indicate again the locations where the pixels fell outside the triangle. The pattern of the EF is roughly the same as the pattern of the TVDI. Again, the northern part is the wettest, where the EF is the largest and the southern part of the field is the driest, where the EF is the smallest. When there is a large EF, it means that the Evapotranspiration is also large.

With Figure 20 we have come as close as possible, with the amount of data that we had, to a spatial Evapotranspiration product. With more data available we could eventually get to this Evapotranspiration product, but for now this is a good first result for an easy way to come as close as possible to this product.

4 Conclusion and recommendations

In this report we have tried to come as close as possible to an easy spatial Evapotranspiration product, by applying the triangle method. With the triangle method we computed the Temperature Vegetation Dryness Index (TVDI) and the Evaporative Fraction. We can conclude that the TVDI that we calculated from this triangle works very well.

We created a universal triangle to be able to calculate the TVDI for any day in any particular year. To do this we used two methods, one where the day LST is used and one where the difference between the day and night LST is used. First, we calculated the TVDI for a large area in the Northern part of Ghana. From this area we determined how well the TVDI worked, based on temporal and spatial correlation.

Based on the temporal and spatial analysis between the TVDI and several other satellite derived dryness index products, we concluded that the performance of the TVDI depends on the time scale, the specific location and the resolution. When looking at the comparison with a shorter time scale, where the TVDI is compared with the TAHMO data, the TVDI performed very well. However, when the time scale increased, with the comparison between the TVDI and the Copernicus data, the TVDI performed less well. The performance increased again when looking at a different location, where the landscape was more homogeneous throughout the year. Problems because of resolution arose when the TVDI was calculated for the drone measurements.

When the TVDI and the Evaporative Fraction were calculated for the drone image, we concluded that there could not be a good validation for how well these two variables performed. This was caused by the little amount of data that we could use to validate the drone outcomes. The universal triangle was constructed with 1km resolution data. It became difficult for the drone, with the higher resolution of 1m, to apply this universal triangle. Therefore the outcomes had to be changed a bit, by looking at a different time slot of the drone, compared with the time the triangle was made. To validate our results, we compared the TVDI with the Copernicus data, but this did not give great results. We already saw that the performance of the TVDI depends on time and space, we therefore need more validation data.

Despite the flaws of the triangle method and the results of the TVDI, we still think this is a good simple method to get a first indication of the spatial variability of the dryness index. The triangle method is a method that uses little amount of data and is therefore applicable in remote areas, which are our study areas.

To increase the performance of the TVDI, we have some recommendations. As already mentioned, more validation data is needed to see how well the TVDI of the drone performs. This can be in the form of a detailed soil moisture index map for the area of the drone. Another option is to make a time series by measuring the soil moisture in the field and comparing it with several images of the drone. Next to more validation data, it is also better to have more drone images. Now only four measurements were made for one particular day and only during the day. Night measurements would be a nice addition to include also the method where the difference between the day and night LST is used. More drone measurements can also be used to make a new triangle with a higher resolution. The triangle that we used during this project had a lower resolution compared with the drone resolution. This resulted in a loss of details. When the triangle is made with the drone measurements it is important to capture a larger area and the landscape throughout the year, to incorporate a lot of different surfaces with different soil moistures. The more detailed triangle will hopefully help by making an even more detailed and correct TVDI of the agricultural field.

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Annex 1 – Overview of sensitivity study

The following table shows the results of the sensitivity study with different percentiles for the edges. When the percentile for the wet edge is varied, the dry edge is taken as a constant and when the percentile for the dry edge is varied, the wet edge is taken as a constant. The constant value is indicated between brackets. This sensitivity study is done for both the methods and the results are shown in Table 1.

Table 1 results of the sensitivity study for the percentiles of the edges.

Edge	Percentile	Method: Day R ²	Method: Day-Night R ²
Wet (Dry = 0.999)	0.05	0.334	0.282
	0.01	0.262	0.217
	0.001	0.173	0.143
Dry (Wet = 0.05)	0.95	0.093	0.169
	0.99	0.188	0.216
	0.999	0.334	0.282

Annex 2 – Extra information for the three different locations

The following figures give some extra information on the location and temporal evolution of the TVDI for the locations 1, 2 and 3. Where location 1 is the TAHMO location, 2 is the location that consist mainly out of agricultural fields and 3 is the location that consist mainly out of savanna.



Figure 25 The exact locations of; 1: the TAHMO station, 2: only agricultural, 3: only savanne.

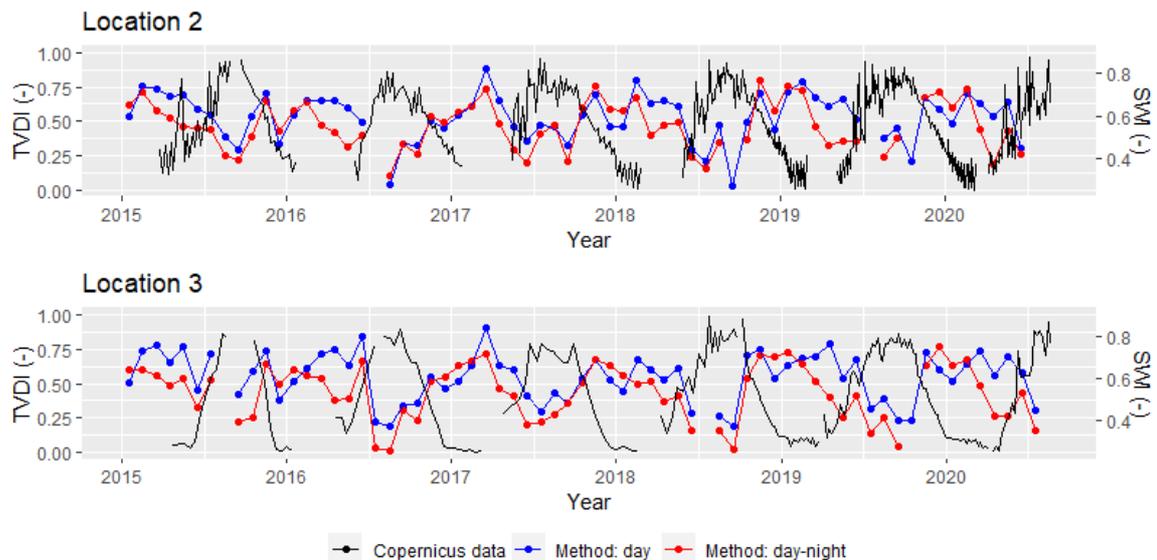


Figure 26 The temporal evolution of the TVDI and the Copernicus SWI during 2015-2020, for location 2 and 3.