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Evaluating the impact of agriculture on albedo using Sentinel-2 data in southern Sweden

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Utvärdering av påverkan av jordbruksmark på albedo med hjälp av Sentinel-2 data i södra Sverige

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Evaluating the impact of agriculture on albedo using Sentinel-2 data in southern Sweden

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Master thesis, 30 credits, in *Physical geography and ecosystem science MSc**

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Abstract

The climate impact of food production plays a big part in the anthropogenic climate impact. Mitigation strategies from this sector are hence of great importance. One area which mainly has been used to calculate climate impact is albedo, the overall reflectance of incoming radiation in all directions. Albedo has been measured for a long time and is vital when calculating the energy balance of an area or biome. It is mainly measured and calculated with the MODIS satellites with a 500 m resolution. This study aims to use the Sentinel-2 spectral instrument with a 10 m resolution to measure the albedo of individual crops effectively. The result shows that the method used to calculate albedo from the Sentinel-2 instrument effectively follows changes in albedo equal to MODIS, for example, changes in seasons over a year. Which means that Sentinel-2 has great potential in being used to give more detailed data with less disturbing factors such as built-up areas, water or other crops within the same pixel. This study also shows differences in albedo between crops, crops and bare soil, and between normal years and years with droughts.

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1. Introduction

Excluding land covered by glaciers, deserts or otherwise barren land, agriculture takes up half of the land on Earth (Ellis et al., 2010; Smith et al., 2018). With a changing climate and high anthropogenic emissions being the driver, it is important to implement mitigation strategies where they are most needed. Since one of the largest impacts of anthropogenic emissions originates from food production (Campbell et al., 2017; Delmotte et al., 2021; Smith et al., 2018), agricultural practices should be a focus area. Of the anthropogenic Greenhouse Gas (GHG) emissions, 26% come from food production (Poore & Nemecek, 2018). This includes the entire supply chain from the fields, transports, and packaging to the final product delivered to consumers. Agricultural practices have also led to multiple changes in biogeochemical cycles, where the global nitrogen (N) cycle has significantly changed due to human agriculture activities. The human alteration of the N-cycle also contributes to GHG emissions through the Haber-Boch process that fixates N from the atmosphere (Swaney et al., 2012). The phosphorous (P) cycle is also heavily modified by human activities, and about 90% of the P is used for agriculture (Cordell & White, 2014). Another example is the freshwater cycle, where large amounts are used for irrigation and livestock (Jägermeyr et al., 2017). However, water usage is within the Planetary Boundary (PB) according to Steffen et al. (2015). The PB for land-system change considers the biophysical aspects of climate change, such as precipitation, evapotranspiration and energy balance (Steffen et al., 2015). One issue is that large forest areas are being converted to agriculture, altering these biophysical variables.

Research on the climate impact of foodstuffs is often conducted through Life Cycle Assessments (LCA). However, LCA rarely uses any energy balance equations, e.g., albedo or calculations of Global Warming Potential (GWP). Two reviews on LCA within food production only mention GWP once, and the subject of albedo or energy balance is not discussed at all (Molina-Besch et al., 2019; Notarnicola et al., 2017). This issue is also brought up by Sieber (2019), who means that most of the LCA are based on annual means of Radiative Forcing (RF) and do not consider any local variability. Sieber et al. (2020) conducted an LCA including albedo to show the GWP of a willow plantation, and among other findings, concluded that willow plantations can help cool the Earth system and that more studies using a similar methodology are needed but with other vegetation types. Other studies have similar findings; a study by Davin et al. (2014) shows that a no-tillage system have a 0.1 higher albedo than a conventional tillage practice. This indicates that a no-tillage systems would be more resistant to heatwaves, which was explained by an asymmetric change in surface albedo during summertime which resulted in stronger impact during extreme temperatures than on average temperatures. Specific crops may also have different effects on albedo, e.g. sugar cane plantation has been shown to increase the albedo when incorporated into the mosaic of a monoculture landscape which in combination with a higher evapotranspiration have shown a local cooling effect (Loarie et al., 2011a).

Albedo is the reflection of incoming radiation in all directions, and it has been estimated or measured for over 100 years. A review by Stephens et al. (2015) found that the earliest paper estimating Earth's albedo is most likely a paper from 1908 written by Abbot, C. G., & Fowle, F. E., (1908). Their estimate has been revised many times since it was conducted before any measurements and was based on assumptions. After Abbot and Fowles's study, albedo has been measured in many ways, e.g. by measurements using balloons (Dines, 1917). The albedo of the Earth has also been estimated by researchers working within the astronomy field (Stephens et al., 2015); they used earthshine observations which were based on the moon's reflection of light to the Earth. With varying results,

these measurements came quite close to the value later measured by satellites (Stephens et al., 2015). One of the first satellite measurements was made by Vonder Haar & Suomi (1971), using data from TIROS-satellites from measurements between 1962 and 1966. They showed an annual average albedo of 0.30 and concluded that the planet was darker and warmer than previous research had shown. In 1996 using the Clouds and Earths Energy System (CERES), the Earth's albedo was once again slightly changed to 0.29 (Wielicki et al., 1996), which is the same as the current measurements of the modern satellites (Stephens et al., 2015). Most of the satellite measurements on albedo are measured with Moderate Resolution Imaging Spectroradiometer (MODIS) with a resolution of 500 m (Schaaf, Crystal & Wang, Zhuosen, 2015a). This resolution is fine when analysing an entire crop system (Sieber, Ericsson, et al., 2022). However, a higher resolution albedo product would be needed for analysis on a smaller scale (Duveiller et al., 2011).

A higher resolution coverage of albedo would provide data sets with less disturbances, from e.g., built up areas, inland water and water ways, and the ability to calculate the albedo for a crop without interference from a different crop on another close by field. This could be done using the Sentinel-2 satellite data with a resolution down to 10 m. It is therefore interesting to use Sentinel-2 data to calculate the albedo on agricultural land to be able to differentiate between crops, without any disturbances from water or built-up areas to test the accuracy of a higher resolution.

1.3 Aim

The aim of this project is to investigate albedo for different crops and bare soils in southwestern Sweden by using Copernicus Sentinel-2 satellite data.

Study questions:

- Can Sentinel-2 be used to measure albedo instead of MODIS?
- What are the differences in albedo between different crops?
- What are the differences in albedo between crops and bare soil?
- What are the effects on albedo in agricultural land in droughts?

2. Theoretical background

2.1 Climate and agriculture in Sweden

According to the classification system Köppen, the majority of Sweden falls within the cold temperate zone, with coniferous forests as the primary biome (SMHI, 2022). The southern part is classified as a warm temperate zone and is dominated by deciduous forests. Global temperature has been increasing with a mean of about 1°C since 1960, which has resulted in melting glaciers, species adapted to warmer climates moving further north and a shorter cold season in the southern areas of Sweden (SMHI, 2022).

The Swedish Board of Agriculture is responsible for controlling the agricultural areas in Sweden (Jordbruksverket, 2021). One of their goals is to create a more sustainable agriculture within the country. Sweden had about 3 million ha of agricultural land in 2019, and the area has declined by more than 70 000 ha since 2010 (Statens jordbruksverk, 2019). Of this area, 1.1 million ha is used to grow ley, used as animal feed. On 990 000 ha, cereals are grown where wheat is the dominating crop.

The last third is divided among several crops; land in fallow 131 000 ha, legumes 44 000 ha, potatoes 23 600 ha, sugar beets 27 300 ha, rapeseed 105 500 ha, and other crops 131 000 ha.

2.2 Radiative forcing

Radiative forcing is the change in the downwelling minus upwelling irradiance caused by an external agent (Solomon et al., 2007). The incoming energy to the Earth system also depends on the location, with the most considerable variations in the latitude (Moene & Dam, 2014).

The downwelling longwave radiation is transformed energy inside the Earth's atmosphere (Moene & Dam, 2014). Many GHGs are efficient absorbers of longwave radiation and emit radiation at the same wavelength (Moene & Dam, 2014). The amount of longwave radiation that reaches the Earth's surface is determined by the temperature and presence of gases that absorb the radiation. This means that longwave downwelling always is present in some way and not depending on the diurnal cycle as shortwave radiation is since the main source is from incoming solar radiance (Moene & Dam, 2014).

2.2.1 Albedo

Albedo is the ratio of exitance and irradiance using all wavelengths in the shortwave spectrum, which is equal to the total radiance of a surface spread across all directions. Albedo is a crucial variable when calculating energy balance or modelling climate (Chuvieco, 2016). Its importance is seen in the energy balance equation (equation 1.3 in Moene & Dam, 2014):

$$\Delta S = Q * -H - L_v E - G + A_h + A_{lat}$$

where ΔS is the change in energy storage, $Q *$ is the net radiation, H is the sensible heat flux, $L_v E$ is the latent heat flux, G is the soil heat flux and A_h and A_{lat} is the net advection energy of the latent and sensible heat flux. In this equation, albedo is a part of the net radiation, $Q *$, which is calculated in the radiation balance equation (Moene & Dam, 2014):

$$Q * = K \downarrow - K \uparrow + L \downarrow - L \uparrow$$

where $K \downarrow$ and $K \uparrow$ is the shortwave down- and upwelling radiation, and $L \downarrow$ and $L \uparrow$, is the longwave down- and upwelling radiation. The albedo is part of the upwelling shortwave flux, $K \uparrow$. Under normal conditions, the Earth is not hot enough to emit shortwave radiation by itself; hence this upwelling comes only from reflected solar radiation (Moene & Dam, 2014). To calculate the albedo, surface properties, zenith and azimuth angles, as well as the incoming radiation is used (Moene & Dam, 2014). Albedo is calculated using two different fractions of the incoming solar radiation, black-sky and white-sky albedo. The black sky-albedo is the directional hemispherical reflectance, which is the surface reflectance when nothing physically blocks incoming solar radiation (Stroeve et al., 2005). White sky-albedo is the bi-hemispherical reflectance, which is the surface reflectance without any direct incoming solar radiation, e.g. diffuse conditions where the incoming radiation is scattered by atmospheric gases (Stroeve et al., 2005). The combination of back-sky and white-sky albedo creates blue-sky albedo (α), which in this text is referred to as albedo (α):

$$\alpha = (1 - D)\bar{\alpha}(\theta_i) + D\bar{\alpha}$$

where D is the diffusion in the atmosphere, θ is the zenith angle as a function of the irradiance (Román et al., 2010). $\bar{\alpha}$ is the black-sky albedo and $\bar{\bar{\alpha}}$ is the white-sky albedo. This means that the blue-sky albedo is a linear weighing between the black-sky and white-sky albedo.

2.3 Satellite Remote Sensing Instruments

2.3.1 MODIS sensor

Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument onboard two of NASA's satellites, Terra and Aqua, which has a revisit time of one to two days and monitors Earth over 36 spectral bands (*MODIS Web*, n.d.). The goal of MODIS is to monitor processes on land, in water and in the lower atmosphere, to predict changes in climate and environment (*MODIS Web*, n.d.). MODIS is also used in generating an albedo product, which derives the albedo from the Bi-directional reflectance distribution function (BRDF) calculations in the 500 m resolution images (Schaaf, Crystal & Wang, Zhuosen, 2015a). The albedo package includes ten black-sky albedo layers and ten white sky-albedo layers, which contain the ten spectral bands used for calculating the albedo (Schaaf, Crystal & Wang, Zhuosen, 2015b).

2.3.2 Sentinel-2 Multispectral Instrument

Sentinel-2 are two of Copernicus, the European space agency's Earth Observing satellites. They have been orbiting Earth since 2015 at an altitude of 786 km (ESA, n.d.-a). They are in a polar orbit, with a revisit time of five days at the equator and have a resolution of 60m, 20m and 10m (ESA, n.d.-a). The Sentinel-2 satellites monitor vegetation, soil, water, inland waterways and coasts. Sentinel-2 measures have 13 spectral bands; four in the 10 m resolution, red, green, blue and near-infrared bands are measured (ESA, n.d.-b). Six bands are used for the 20 m resolution: four narrow bands in the visible and near-infrared spectra and two shortwave infrared bands. The 60 m resolution carries three bands focused on clouds, aerosols, water vapour, cirrus and atmospheric correction (ESA, n.d.-b).

3. Methodology

The albedo was calculated from Sentinel-2A data using the narrow-to-broadband method from Bonafoni & Sekertekin (2020) (see section 3.2.2), and MODIS data was used to validate these calculations. No correction for BRDF was done as this is a complex method that is not within the scope of this study. The affect that BRDF has on the albedo has also been discussed and might not have a big impact (Tian et al., 2021).

In Sweden, the crops on agricultural fields must be reported to the Board of Agriculture. This data has been used to identify where different crops are grown to enable spotting differences in the albedo between different crops or bare soil.

3.1 Study area

The location is from the grid cell T33UUB from the Copernicus Sentinel-2 satellite. The area includes a part of Denmark, Öresund and the southwestern part of Skåne in Sweden. This area was cropped so that only a 10x10 km area in southwestern Skåne was included (See figure 1). The Skåne area was

chosen as it is an important agricultural area and is responsible for about 50% of Swedish food production (*Livsmedel och jordbruk - Utveckling Skåne*, n.d.). The smaller area was chosen as there are no larger towns or cities nearby, and it consists mainly of agricultural land.

Map showing the location of the study area

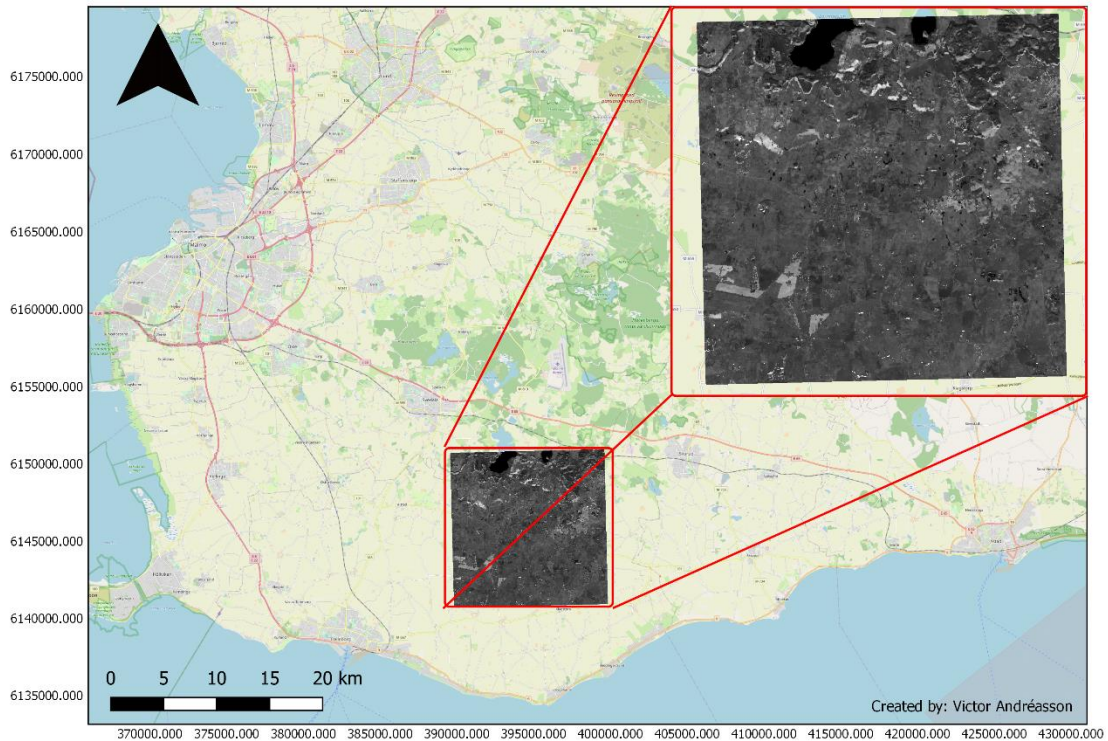


Figure 1. Shows the study location in the Skåne region in the south of Sweden. With a total area of 10x10 km.

3.2 Satellite and field data

Sentinel-2 level 2A surface reflectance was downloaded from Creodias, containing all the wavelengths from the Sentinel-2 instrument (See section 2.3.2) and dates from 2017 – 2020.

The MODIS product MCD43A3 was downloaded from NASA, with the premade albedo calculations for 2017 – 2020. From the MODIS data white-sky and black-sky albedo was used.

Crop-type and location data was obtained from Naturvårdsverket in the form of GIS shapefiles. This data was used in two ways; a few common crops were selected to be analysed in more depth, and the combination of crops, including not only the selected crops but all crops in the area.

3.3 Data preparation

With a large amount of data, its preparation, calculation, and analysis needed to be automated. This was done using QGIS and Matlab.

3.3.1 Extraction and preparation of Sentinel-2 and MODIS data

First, the data was extracted and cropped (code in Appendix 1.), so only the area in figure 1 remained. To test the method, ten pixels from the Sentinel dataset equal to an area of 100x100 m located on agricultural land were used to run through the model. After that it was scaled up to the entire area.

The used bands include four 10m resolutions (bands 2,3,4 and 8. See Table 1) and two 20-m resolutions (bands 11 and 12. See Table 1), which need to be calculated together. Therefore the 20-m bands had to be sub-sampled to fit the 10m bands before they could be incorporated into the equation, which means that the 20 m pixels were split to be the same size as the 10 m pixels.

A smoothing spline was run through both the Sentinel-2 and MODIS data to eliminate any outliers and fill gaps that occur in the data due to cloudy conditions or because of the satellite's revisit time. The smoothing spline with a smoothing parameter of 1,000 was chosen as this has been proven to reduce data noise and maintain a certain level of variability during the growing season (Cai et al., 2017).

3.3.2 Calculating the albedo

To convert the downloaded Sentinel-2 L2A surface reflectance from 0 – 10 000 to 0-1, a multiplication factor of 0.0001 was applied. The albedo calculations are based on a study by Bonafoni & Sekertekin (2020), where the blue, green, red, near-infrared and two shortwave infrared bands have been used in the calculations (see Table 1). The weighting coefficient is also calculated by Bonafoni & Sekertekin (2020) using the following equation:

$$\omega B = \frac{\int_{LB}^{UB} R_{s\lambda} * d\lambda}{\int_{0.3}^3 R_{s\lambda} * d\lambda}$$

where UB and LB are the upper and lower wavelengths for each band (table 1), $R_{s\lambda}$ is the spectral solar radiation at Earth's surface, and $d\lambda$ is the differences in the wavelengths. The wavelength endpoints for the bands used are 3 and 0.3 (table 1).

To calculate the albedo the following equation was used:

$$\alpha = \sum_{B=1}^n \rho B * \omega B$$

where ρB is the measured reflectance for each band and ωB is the weighting coefficient.

Table 1. The spectral bands with the band name from Sentinel-2 (B2 – B12), Upper and lower wavelengths, central wavelengths and weighting coefficients (Bonafoni & Sekertekin, 2020a).

Band	Upper wavelength	Lower wavelength	Central wavelength	Weighting coefficient
B2 – Blue	0.3	0.533	0.492	0.2266
B3 – Green	0.533	0.614	0.559	0.1236
B4 – Red	0.614	0.730	0.665	0.1573
B8 – NIR	0.730	1.226	0.833	0.3417

B11 – SWIR	1.226	1.88	1.612	0.1170
B12 – SWIR	1.88	3	2.194	0.0338

The Start of Season (SoS) and End of Season (EoS) were used instead of taking the entire year of albedo data from the fields. This was done to exclude bare soil at the beginning and end of the year. To get the SoS and EoS dates Normalised Difference Vegetation Index (NDVI) was used. This was done using NDVI data from Google Earth Engine, which was processed and compared to the albedo data in Matlab. An NDVI value above 0.2 was selected as SoS, and below set the EoS. This was done for each crop individually, assuming that the growth cycles of the same crop are closely similar within the study area. The same was done for bare soil to ensure no vegetation was included here, but only for land reported to the board of agriculture as land left in fallow with no cover crop and with an NDVI below 0.2.

3.3.3 Atmospheric correction

The atmospheric correction is already premade on the Creodias site, and one of the outputs from this correction is a scene classification layer (SCL) (*Sen2Cor – STEP*, n.d.). The SCL classifies all the pixels in an image into different categories (table 2). This makes it possible to select only the necessary output for this study. The areas included in this study were vegetation and non-vegetated land (4 & 5 in Table 2), which excludes all other classes.

Table 2. *Sen2Cor image classification classes for the sentinel-2 satellite instrument (Sen2Cor – STEP, n.d.).*

Label	Classification
0	No data
1	Saturated or defective
2	Dark area pixels
3	Cloud shadows
4	Vegetation
5	Not vegetated
6	Water
7	Unclassified
8	Cloud medium probability
9	Cloud high probability
10	Thin cirrus
11	Snow

3.3.4 Matching crop type data to satellite images

To pinpoint the specific crops in the images the albedo data and the reported crops had to be matched up and the cells split up to create new matrixes of the albedo data for each crop. This was done using QGIS. First, to match the two layers, the crop data coordinate systems were changed from ESPG:3006 to the same as the albedo raster layer, ESPG:32633. The second part was made in Matlab, where the two data sets were matched up, and the coordinates of each cell in the albedo data were compared to the same cell in the crop data. Each cell was divided into a new matrix depending on this comparison. One additional category was created that included all the crop codes except for the one for fallow without a cover crop, i.e., bare soil.

3.4 Data analysis

To quantify the results a permutation test was used (Laurens, 2023). This test was adequate since the data is not normally distributed, and the variables all have different sample sizes. The null hypothesis

is that there are no differences in the datasets. A permutation test runs through all possible permutations several times, meaning that the test shuffles the data. For this study, 10 000 permutations were selected. If the shuffling of the datasets does not matter, the null hypothesis cannot be rejected. The output from the test gives a P-value, indicating the differences in the mean values between the dataset and the effect size based on Hedges'g and which is the real difference between the data sets.

3.4.1 Validation of the method

For validating the Sentinel-2 albedo calculations, MODIS data were used. One MODIS pixel was selected, which has an area of 500x500 m. The same area was selected for the Sentinel-2 data. The MODIS data is divided between black-sky albedo and white-sky albedo; both have been individually tested against the Sentinel-2 albedo. The data sets were compared with a correlation test to see how well they matched. A permutation test was also performed to check for any bias in the data and root mean square error (RMSE). The variance and the mean value within both datasets were also calculated.

3.4.2 Statistical analysis of crops

The crop data were analysed using a time series graph, a permutation test and RMSE to investigate the differences between the selected crops and the difference between all crops in the area and bare soil. A permutation test and RMSE were used for the differences between the years. A mean value and variance are also used for all the variables.

4. Results

This project used an area of 10 x 10 km in the region of Skåne in Sweden. This gives a total of 10 000 Ha, which, apart from agriculture, also includes forests, lakes, roads, and built-up areas. The area of the selection of crops and bare soil can be seen in Figure 2. Sugar beets are consistently the most common of these crops in the area. Ley and bare soil are doing some small shifts throughout the years. The area of barley, spring wheat, and oats are shifting more.

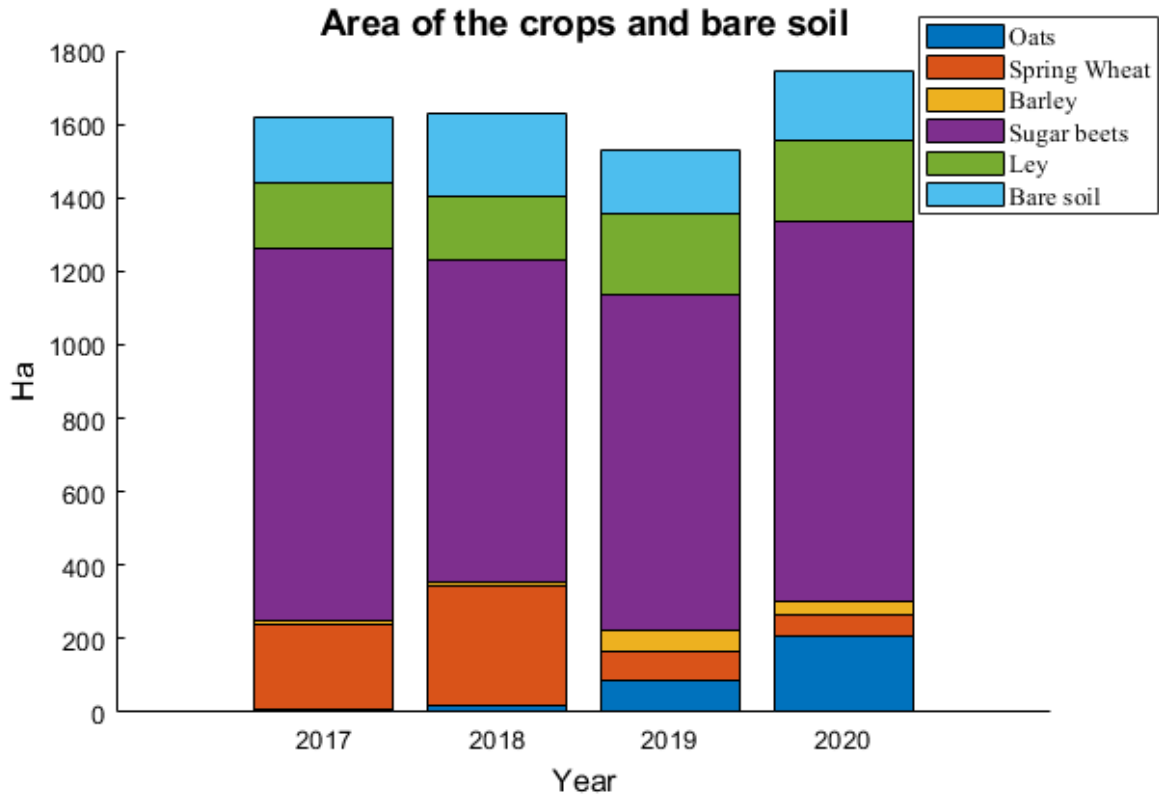


Figure 2. The area of land used for the investigated crops in this study and bare soil.

4.1 Validation of the method

The Sentinel-2 albedo calculations were compared to the premade albedo calculations from MODIS (Figure 4). This was done on one MODIS pixel of 500x500 m, this was compared with the mean albedo of the same area for the corresponding 50 pixels from the Sentinel-2 data. The Sentinel-2 albedo calculation follow the trend of the white-sky albedo (WSA) and the correlation coefficient here is 0.81 for the WSA in combination with the P-value from the permutation test confirms this. The black-sky albedo (BSA) correlation coefficient is 0.35. During the off-season, the trends for the Sentienel-2 have a lower minimum albedo and seem to increase quite rapidly again. The MODIS data have a higher minimum value and are more stable for longer. Opposed from both the Sentinel-2 and the WSA there is a peak for the BSA during the winter months of 2018.

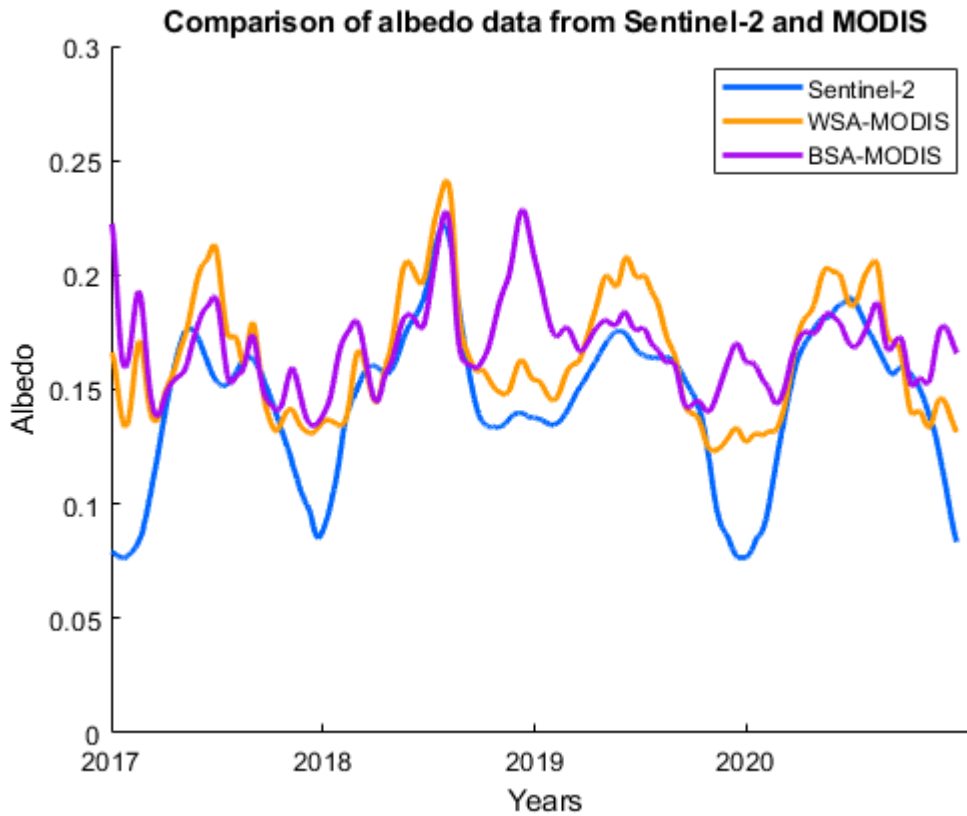


Figure 3. Albedo data of Sentinel-2 and MODIS compared over time, starting on the 1st of January 2017 and the last day being the 31st of December in 2020. The Sentinel-2 data is an average of the area, and the MODIS data is the data measured by the satellite divided into black-sky albedo (BSA-MODIS) and white-sky albedo (WSA-MODIS).

The differences between the two ways of retrieving albedo data are quantified in Table 3. The P-value is 0.0001 when comparing Sentinel-2 to both the BSA and WSA, meaning there is a significant difference between the Sentinel-2 data and the MODIS data. This is also seen in Table 4, where the mean values have a difference of 0.02.

Table 3. Permutation test of the differences between the Sentinel-2 albedo calculations and albedo from MODIS.

Permutation test for the different instruments				
Run	Significance (p < 0.05)	Effectsize (Hedges'g)	RMSE	Sample size
Sentinel-2 vs WSA	0.0001	-0.6340	0.0273	1460
Sentinel-2 vs BSA	0.0001	-0.8811	0.0369	1460

Table 4. Variance and mean albedo values for the Sentinel-2 and the MODIS albedo data.

Statistics Instruments		
Instrument	Variance	Mean
S2	0.00098	0.14624

MODIS WSA	0.00075	0.16452
MODIS BSA	0.00035	0.16900

4.2 Albedo differences between the crops

Figure 3 shows the selected crop's albedo over the growing season for each year. The average albedo of oats seems to have similar values through the measured time, with a slight decline in 2020. The highest albedo of the oats was in 2019 at 0.2. For spring wheat, the values seem to vary a bit, with an overall lower albedo in 2020 and no clear peak as for the other years. As for oats, spring wheat had its highest albedo in 2019, with an albedo of 0.21. The albedo for barley is among the crops with lower values for 2017, 2019 and 2020 but had a higher peak in 2018. The peak in 2018 reached an albedo of 0.24, the highest among the investigated crops. Sugar beets (SB) have a similar trend each year. It is consistently above 0.2 in albedo, with the exception being 2018. Ley, which has a high ground cover, is the only crop consistently above 0.2 for all the years, including 2018.

The days when the when peak albedo occurs varies between the start of May to the start of September. During 2018 the peak date seems to be in a narrower period where most crops have peak albedo in August, except ley, which peak in May. Ley is consistently the crop with the earliest peak in albedo and has its latest peak on the 3rd of June in 2017. Oats have the latest peak, happening on the 7th of September in 2017. It is also the crop with the most fluctuating peak dates, since oats also have the earliest peak of all crops on the 6th of May in 2019.

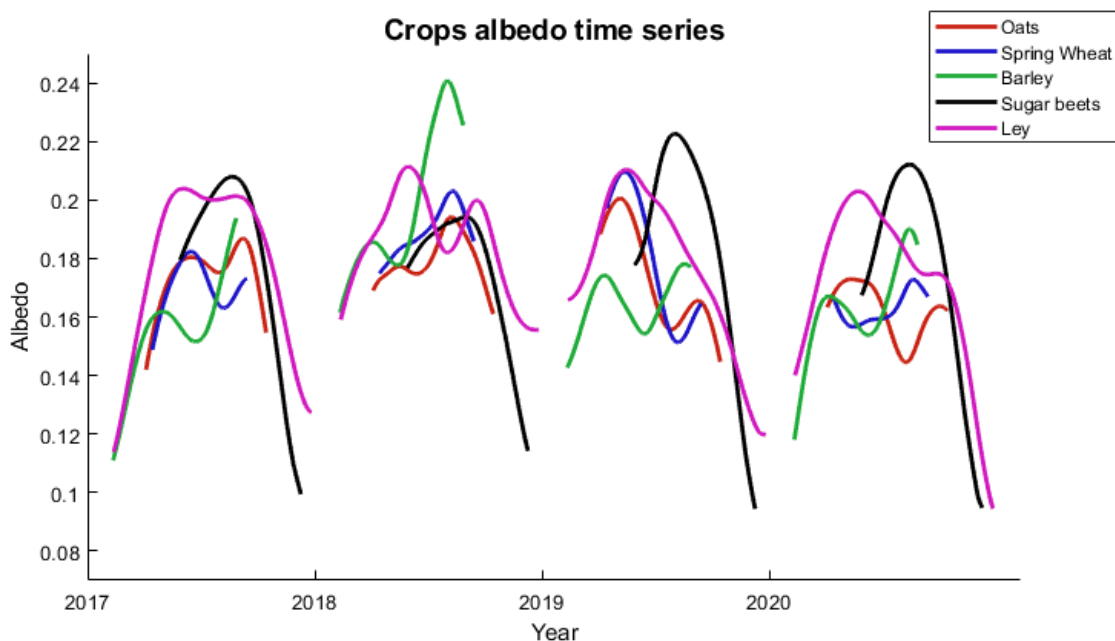


Figure 4. The average albedo of the investigated crops between 2017 and 2020.

Looking at the differences between the crops there is a significant difference in the albedo between all the selected crops, with one exception (Table 3). The only crops that are not significantly different in albedo are sugar beets and ley; with a P-value of 0.55, the albedo of these two crops is similar. In this instance, this is also backed up by the mean value, which differs with 0.007 (Table 4). The other crops

also have similar mean values. However, the distribution and spread of the albedo is big enough that there is a difference.

Table 5. Permutation test values comparing the investigated crops, showing *P*-value, effect size, the observed difference, RMSE and the size of the crops.

Permutation test for the crops				
Run	Significance (p < 0.05)	Effectsize (Hedges'g)	RMSE	Sample size
Oats vs SW	0.0001	-0.2262	0.0106	1460
Oats vs Barley	0.0156	0.1224	0.0241	1460
Oats vs SB	0.0001	-0.2554	0.0336	1460
Oats vs Ley	0.0001	-0.2786	0.0238	1460
SW vs Barley	0.0001	0.2792	0.0229	1460
SW vs SB	0.0389	-0.1163	0.0345	1460
SW vs Ley	0.0328	-0.1062	0.0259	1460
Barley vs SB	0.0001	-0.3048	0.0352	1460
Barley vs Ley	0.0001	-0.3242	0.0304	1460
SB vs Ley	0.5537	0.0254	0.0209	1460

Table 6. Variance and mean values for each of the investigated crops.

Statistics crops		
Crop	Variance	Mean
Oats	0.0002	0.1724
Spring wheat	0.0003	0.1757
Barley	0.0006	0.1700
Sugar beets	0.0011	0.1787
Ley	0.0006	0.1780

4.3 Differences between crops and bare soil

All crops in the area are compared to the bare soil. Bare soil continuously has a higher peak in albedo than the crops (Figure 3). Bare soil peaked at 0.24 on the 16th of June in 2017 and had a lower peak in 2018 on the 19th of June with an albedo of 0.204. The highest peak for bare soil happens in 2019, with an albedo of 0.27 on the 15th of July. For 2020 the peak happened on the same date as the previous year but at a lower albedo of 0.21. For the albedo of the crops, the peaks are lower and happen later during the summer. The peak for 2017 is at 0.18 on the 26th of August. For 2018 the peak happens on the 31st of July at 0.2. In 2019 the 21st of May with a peak at 0.18, and in 2020 the peak happens 13th of May at 0.17. The crops have an albedo which seems to have the same trend for the normal years, but for the drought year in 2018, there is a peak which is higher than the normal years, where the peak for bare soil is lower. For the wintertime, it seems like the crops have a slightly higher mean albedo; this can be seen clearer during winter 2018/2019.

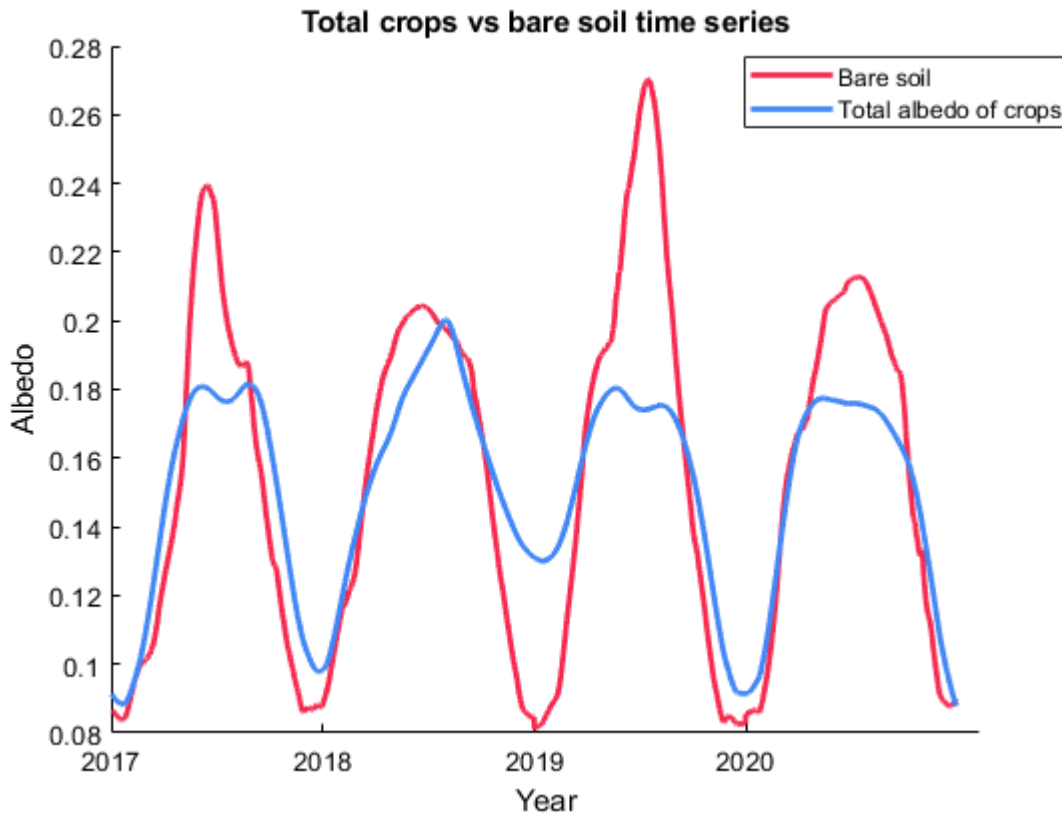


Figure 5. Time series showing the albedo of all crops in the area and the albedo of bare soil between 2017 – 2020.

The differences between the crops and bare soil are significant, with a P-value of 0.037 (Table 5), meaning that bare soil has a higher albedo than the combined albedo of crops. Despite similar mean values, the differences are in the albedo distribution over time since the mean values are quite close (Table 6).

Table 7. Permutation test values comparing the total albedo of all crops in the area with bare soil. Showing P-value, effect size, the observed difference, RMSE and the sample size.

Permutation test for total albedo and bare soil				
Run	Significance (p < 0.05)	Effectsize (Hedges'g)	RMSE	Sample size
Total albedo of crops vs Bare soil	0.0373	-0.0769	0.0283	1460

Table 8. Variance and mean values for the total crops in the area and bare soil.

Statistics crops and bare soil		
Crop	Variance	Mean
Total albedo of crops	0.0009	0.1507
Bare soil	0.0026	0.1540

4.4 Drought effect on albedo

The albedo from 2017, 2019 and 2020 differ significantly from the albedo during 2018 (Table 7). There is also a significant difference in the albedo between 2017 and 2019. This is the only instance where there is a difference between the 'normal'-years. The differences in the mean values are quite close. However, there are differences to be seen, e.g. between 2017 and 2018, which have a difference of 0.0155 (Table 8).

Table 9. Permutation test values of all crops in the area compared between different years.

Permutation test for the years				
Run	Significance (p < 0.05)	Effectsize (Hedges'g)	RMSE	Sample size
2017 vs 2018	0.0001	-0.4916	0.0193	365
2017 vs 2019	0.0038	-0.2156	0.0190	365
2017 vs 2020	0.0650	-0.1366	0.0114	365
2018 vs 2019	0.0001	0.3118	0.0204	365
2018 vs 2020	0.0001	0.3724	0.0165	365
2019 vs 2020	0.2928	0.0777	0.0133	365

Table 10. Variance and mean albedo values for all crops in the area for the years.

Statistics years		
Year	Variance	Mean
2017	0.0012	0.1441
2018	0.0007	0.1594
2019	0.0008	0.1508
2020	0.0009	0.1486

5. Discussion

5.1 Validation of the Sentinel-2 data

The MODIS albedo seems to validate the Sentinel-2 albedo calculations made within this study quite well. The two datasets follow the same seasonal variability but still have significant differences. These differences may have multiple sources. First, they have very different resolutions; the 500m resolution of the MODIS data gives coarser data, and the higher resolution of 10m from the Sentinel-2 albedo generates a more detailed data. Secondly, the calculations made to retrieve the albedo are different MODIS use the ten spectral band whereas the method used in this study by Bonafoni & Sekertekin, (2020b) uses six spectral bands. MODIS calculates the white-sky and black-sky albedo separately and the Sentinel-2 calculations result in the blue-sky albedo right away. A third difference is that no BRDF calculation was made in this study, which provides a certain risk of error even though the impact of this might not be significant (Tian et al., 2021).

So, the results of these tests are expected to differ. The most important part of the validation is to see that the trends are accurate, as seen in the time series figure (Figure 4) and with the correlation coefficient of 0.8. This means that the calculations of albedo made from the Sentinel-2 data in this study are viable for investigating the crops and the yearly differences in albedo. Moreover, it means that the albedo of the mosaic patterns of the Swedish monocultures can be analysed on a large scale using the higher resolution of the Sentinel-2 satellites compared with the coarser resolution from the MODIS satellites that are more commonly used. Future studies should look closer to the impact of BRDF on surface albedo of Sentinel-2 data to improve the calculations further.

5.2 Differences between the crops

The crops investigated closer in this study all seem to have similar trends in the time series (Figure 1), with similar mean values. However, there are only two of the crops that have no significant difference, ley and sugar beets. Both ley and sugar beets are consistently among the crops with the highest peak in albedo, except for barley in 2018. The other crops differ significantly. This difference is explained by how the albedo changes over the season. There are also significant differences between crops which are quite similar, e.g., barley, spring wheat and oats. These cereals are similar in some ways since they are all part of the grass family. However, this study still finds significant differences between these crops. They may act differently when exposed to stresses such as droughts or heatwaves, which could explain the difference. Another possible explanation could be the impact of post-harvest management or species-specific phenology (Sieber, Böhme, et al., 2022). These findings indicate that the crops matter for the amount of reflected energy. Other studies have found similar results where specific crops locally have contributed to a decrease in temperature, for example, the study on sugar cane by Loarie et al. (2011b). The significant differences between the crops mean that albedo has a vital role in the climate impact of crops. Hence it is important to consider the albedo of different crops when looking at mitigation strategies (Sieber, Ericsson, et al., 2022; Zhang et al., 2022).

Using albedo in LCA would provide a more accurate carbon footprint of a product. For example, a study by Muñoz et al. (2010) showed that taking albedo into account of tomatoes grown in a greenhouse lowered the calculated climate impact with almost 140 kg of CO₂ equivalents/ ton of produce. This means that albedo has to be considered no matter which crop system is used, including monocultures, no-tillage systems, agroforestry systems, greenhouses or any other farming practice. This would result in clear information on the climate impact of a product and theoretically provide an easier way for consumers to choose the foodstuffs with a lower climate impact. This is backed up by Zhang et al. (2022), who show that including albedo would cause less contradicting results from LCA.

Even though this study finds significant differences between the albedo in most crops, it is essential to keep a broad perspective. There are, of course, multiple vital aspects to consider when analysing the impact of agriculture. This study focuses on the climate impact; however, the environmental impact is just as significant and should not be forgotten. For example, biodiversity and soil health are important factors in resilient agriculture (Shahmohamadloo et al., 2022). Possibly, the cooling effect of a higher albedo could be helpful when it comes to restoring biodiversity and soil health, since it might keep important biomes from being destroyed. This is something that further research could test. Furthermore, future studies should test for correlations between albedo and LAI or NDVI, to see whether ground cover is related to albedo in any way.

5.3 Differences between crops and bare soil

The bare soil albedo is significantly higher than the crops every year except for 2018 during the drought. This finding differs slightly from the finding of Sieber, Böhme, et al. (2022), who found a bare soil albedo of 0.13, whereas in the present study, the mean bare soil albedo is 0.154 and peaks above 0.2 every summer. What this difference depends on could be many factors. The years are the same as in this study but only 2019-2020. However, in a more northern location in the middle of Sweden, which means that there might be differences in soil types, temperatures, incoming radiation and possibly a higher soil water content, all of which are correlated with albedo (He et al., 2019; Loeb et al., 2017). For example, with a higher soil water content a lower albedo would be expected. What does this mean for the region of Skåne? With a higher albedo of bare soil than for the crops, a comparison of the total climate impact of a growing crop and a field left in fallow with no cover crop needs to be done. Lintunen et al. (2022) studied the effects of albedo and increase in mass of a coniferous forest with a low albedo in Finland and concluded that the negative effect of the low albedo on the climate was less than the positive effect of the carbon bound from the atmosphere. Making a similar study on crops and bare soil in comparison would be vital to see the net climate impact to determine the driving factor for climate change in the area.

5.4 Differences between the years and effects of the drought

The results show clear evidence that the drought affects the albedo of crops, with an albedo significantly higher during the drought year. This could possibly be explained by low harvests and more exposed bare soil. Then again, the higher albedo could be explained by its correlation with soil water content; lower soil water content would give a higher albedo value. Extreme weathers, such as heatwaves and droughts, are predicted to occur more frequently (Delmotte et al., 2021). These extremes are a threat to the production of food. New ways to adapt and mitigate the effects of, e.g. droughts are needed (Bennett et al., 2014). It might be possible to use albedo to lower some of the highest temperatures during a heatwave and thus mitigate some of the effects of a heatwave, maybe using something similar to the white plastic covers farmers in Skåne use on potato fields to retain some of the moisture to the land, the bright surface should also raise the albedo of the field. If albedo could be used in this manner, albedo would also be a question of food security.

5.5 Potential sources of error

When analysing the crops in this study, there has been no account for the temperature, weather or soil type differences. This poses a potential source of error and could affect the albedo of the crops. However, the area is relatively small and should have similar weather conditions. Three different soil types dominate, spread out over the area (Daniel et al., 2000), which means that the crops grown here should be spread out over the different soil types and have a minimal effect on the result. Another thing that might affect the results is the difference in the areal coverage of the crops. Comparing some of the crops, e.g. barley which consistently has a smaller area, to sugar beets which consistently have a bigger area, might affect the results because the data sets are of different sizes. Further irrigation has not been included in the data for the fields, which could mean that there are more to the results that is not seen. Further Sentinel-2 albedo studies on droughts could look closer at the effects of irrigation on agricultural fields during a drought year which would provide important information on its effect.

5.6 Conclusions

Differences in albedo were found in between different crops, crops and bare soil, and between normal years and years of drought. With these results this project shows that there is great potential in using the Sentinel-2 for albedo calculations. The versatility of the higher resolution compared to the MODIS data works well when analysing larger areas and being able to crop out excess data. Using Sentinel-2 albedo calculations could help policymakers in decision making and could thus be a part of creating a more sustainable food system. Further research should focus on getting more precise albedo calculations with Sentinel-2, for example comparing Blue-sky albedo to blue-sky albedo and investigating the impact of BRDF on albedo.

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Appendix 1

```
%% Script to import, calculate and display albedo values

% Script developed by Victor Andréasson 2022-2023
% credits: Zhanzhang Cai & Joanna Eaton

%% Decides a folder for all the outputs and settings for running the script

clear
close all

% Folder where all output will be saved:
outputfolder = ['T:\Ex-jobb_VictorAndréasson\Results'];

% Years that will be processed:
yr = 2017:2020;

%% Script for importing & calculating albedo
% Script for calculating albedo for all crops, total albedo and bare soil.

% For i: this part imports, extracts and cuts the data to the study area
% For ii: sets nan-values, calculates the correct fraction and separates
% all the crops with SoS and EoS.

for i = yr
    i
    files = dir(['T:\Ex-
jobb_VictorAndréasson\data\daily_albedo_sub\daily_albedo_sub\albedo_',num2str(i),*.tif']);
    files_NDVI = dir(['T:\Ex-
jobb_VictorAndréasson\data\daily_ndvi_sub\daily_ndvi_sub\ndvi_',num2str(i),*.tif']);
    croptype = imread(['T:\Ex-jobb_VictorAndréasson\data\Crops-Skane17-20\crop',num2str(i),'.tif']);
    croptype = croptype(5000:6000,3000:4000);    % Modifying croptype to fit with the albedo &
NDVI data.

    for ii = 1:length(files)
        ii
        albedo = geotiffread(fullfile(files(ii).folder,files(ii).name));
        NDVI = geotiffread(fullfile(files_NDVI(ii).folder,files_NDVI(ii).name));

        albedo = cast(albedo,'single');    % Convert to be able to set NaN-values.
        NDVI = cast(NDVI,'single');

        albedo(albedo == -9999) = nan;
        NDVI(NDVI == -9999) = nan;

        albedo = albedo / 10000;    % Divides to get the correct fraction.
```

```

NDVI = NDVI / 10000;           % Divides to get the correct fraction.

% Creates a year matrix and a day of year matrix:
y = i;
doy = str2double(files(ii).name(end-6:end-4));
t{i-yr(1)+1}(ii) = datetime(datestr(datenum(y,1,1)+doy-1));

% Calculates the area for each crop, once per year. Both in
% percentage and Ha.
if ii == 1
    Ha_oats{i-yr(1)+1}(ii) = ((length(albedo(croptype==3))*100)/10000);
    Ha_SW{i-yr(1)+1}(ii) = ((length(albedo(croptype==5))*100)/10000);
    Ha_barley{i-yr(1)+1}(ii) = ((length(albedo(croptype==8))*100)/10000);
    Ha_SB{i-yr(1)+1}(ii) = ((length(albedo(croptype==47))*100)/10000);
    Ha_ley{i-yr(1)+1}(ii) = ((length(albedo(croptype==50))*100)/10000);
    Ha_BS{i-yr(1)+1}(ii) = ((length(albedo(croptype==60))*100)/10000);
end

% Choses the files for each crop based on the SoS and EoS, matches
% the croptype for albedo & reflectance and calculates the mean value:
if ii > datenum(2019,04,03)-datenum(2019,1,1)+1 & ii < datenum(2019,10,15)-
datenum(2019,1,1)+1
    avg_oats{i-yr(1)+1}(ii) = nanmean(albedo(croptype==3));
    err_1a{i-yr(1)+1}(ii) = nanmean(albedo(croptype==3)) + std(albedo(croptype==3)); %
Higher limit of std
    err_0a{i-yr(1)+1}(ii) = nanmean(albedo(croptype==3)) - std(albedo(croptype==3)); %
Lower limit of std
else
    avg_oats{i-yr(1)+1}(ii) = nan;
    err_1a{i-yr(1)+1}(ii) = nan;
    err_0a{i-yr(1)+1}(ii) = nan;
end

if ii > datenum(2019,04,13)-datenum(2019,1,1)+1 & ii < datenum(2019,09,14)-
datenum(2019,1,1)+1
    avg_SW{i-yr(1)+1}(ii) = nanmean(albedo(croptype==5));
    err_1b{i-yr(1)+1}(ii) = nanmean(albedo(croptype==5)) + std(albedo(croptype==5));
    err_0b{i-yr(1)+1}(ii) = nanmean(albedo(croptype==5)) - std(albedo(croptype==5));
else
    avg_SW{i-yr(1)+1}(ii) = nan;
    err_1b{i-yr(1)+1}(ii) = nan;
    err_0b{i-yr(1)+1}(ii) = nan;
end

```

```

    if ii > datenum(2019,02,09)-datenum(2019,1,1)+1 & ii < datenum(2019,08,28)-
datenum(2019,1,1)+1
        avg_barley{i-yr(1)+1}(ii) = nanmean(albedo(croptype==8));
        err_1c{i-yr(1)+1}(ii) = nanmean(albedo(croptype==8)) + std(albedo(croptype==8));
        err_0c{i-yr(1)+1}(ii) = nanmean(albedo(croptype==8)) - std(albedo(croptype==8));
    else
        avg_barley{i-yr(1)+1}(ii) = nan;
        err_1c{i-yr(1)+1}(ii) = nan;
        err_0c{i-yr(1)+1}(ii) = nan;
    end

    if ii > datenum(2019,05,28)-datenum(2019,1,1)+1 & ii < datenum(2019,12,10)-
datenum(2019,1,1)+1
        avg_SB{i-yr(1)+1}(ii) = nanmean(albedo(croptype==47));
        err_1e{i-yr(1)+1}(ii) = nanmean(albedo(croptype==47)) + std(albedo(croptype==47));
        err_0e{i-yr(1)+1}(ii) = nanmean(albedo(croptype==47)) - std(albedo(croptype==47));
    else
        avg_SB{i-yr(1)+1}(ii) = nan;
        err_1e{i-yr(1)+1}(ii) = nan;
        err_0e{i-yr(1)+1}(ii) = nan;
    end

    if ii > datenum(2019,02,10)-datenum(2019,1,1)+1 & ii < datenum(2019,12,27)-
datenum(2019,1,1)+1
        avg_ley{i-yr(1)+1}(ii) = nanmean(albedo(croptype==50));
        err_1f{i-yr(1)+1}(ii) = nanmean(albedo(croptype==50)) + std(albedo(croptype==50));
        err_0f{i-yr(1)+1}(ii) = nanmean(albedo(croptype==50)) - std(albedo(croptype==50));
    else
        avg_ley{i-yr(1)+1}(ii) = nan;
        err_1f{i-yr(1)+1}(ii) = nan;
        err_0f{i-yr(1)+1}(ii) = nan;
    end

    avg_BS{i-yr(1)+1}(ii) = nanmean(albedo(croptype==60 & NDVI<0.2)); % Bare soil set as
fallow land with less than 0.2 NDVI
    err_1g{i-yr(1)+1}(ii) = nanmean(albedo(croptype==60 & NDVI<0.2)) +
std(albedo(croptype==60));
    err_0g{i-yr(1)+1}(ii) = nanmean(albedo(croptype==60 & NDVI<0.2)) -
std(albedo(croptype==60));

    avg_TA{i-yr(1)+1}(ii) = nanmean(nanmean(albedo(croptype~=60))); % runs as long as
croptype is not == 60.
    err_1h{i-yr(1)+1}(ii) = nanmean(nanmean(albedo(croptype~=60)) +
std(albedo(croptype~=60)));
    err_0h{i-yr(1)+1}(ii) = nanmean(nanmean(albedo(croptype~=60)) - std(albedo(croptype~=60)));
end
end

```



```

%% Statistics
% Runs a permutation test (must have the permutationTest.m function in the
% same folder. This outputs a P-value, the observed difference and an
% effect size based on Hedges'g.
%
% RMSE is also calculated for the differences bewteen the crops as well as
% variance and mean value for the individual crops.

% Data preperation, converts from cell to be able run calculations:
avg_oats = cell2mat(avg_oats);
avg_SW = cell2mat(avg_SW);
avg_barley = cell2mat(avg_barley);
avg_SB = cell2mat(avg_SB);
avg_ley = cell2mat(avg_ley);
avg_BS = cell2mat(avg_BS);
avg_TA = cell2mat(avg_TA);

Ha_oats17 = cell2mat(Ha_oats(1));
Ha_oats18 = cell2mat(Ha_oats(2));
Ha_oats19 = cell2mat(Ha_oats(3));
Ha_oats20 = cell2mat(Ha_oats(4));

Ha_SW17 = cell2mat(Ha_SW(1));
Ha_SW18 = cell2mat(Ha_SW(2));
Ha_SW19 = cell2mat(Ha_SW(3));
Ha_SW20 = cell2mat(Ha_SW(4));

Ha_barley17 = cell2mat(Ha_barley(1));
Ha_barley18 = cell2mat(Ha_barley(2));
Ha_barley19 = cell2mat(Ha_barley(3));
Ha_barley20 = cell2mat(Ha_barley(4));

Ha_SB17 = cell2mat(Ha_SB(1));
Ha_SB18 = cell2mat(Ha_SB(2));
Ha_SB19 = cell2mat(Ha_SB(3));
Ha_SB20 = cell2mat(Ha_SB(4));

Ha_ley17 = cell2mat(Ha_ley(1));
Ha_ley18 = cell2mat(Ha_ley(2));
Ha_ley19 = cell2mat(Ha_ley(3));
Ha_ley20 = cell2mat(Ha_ley(4));

Ha_BS17 = cell2mat(Ha_BS(1));
Ha_BS18 = cell2mat(Ha_BS(2));
Ha_BS19 = cell2mat(Ha_BS(3));
Ha_BS20 = cell2mat(Ha_BS(4));

```

```
Ha_crops = [Ha_oats17 Ha_SW17 Ha_barley17 Ha_SB17 Ha_ley17 Ha_BS17; Ha_oats18 Ha_SW18
Ha_barley18 Ha_SB18 Ha_ley18 Ha_BS18; Ha_oats19 Ha_SW19 Ha_barley19 Ha_SB19 Ha_ley19
Ha_BS19; Ha_oats20 Ha_SW20 Ha_barley20 Ha_SB20 Ha_ley20 Ha_BS20];
```

```
% Permutation test:
```

```
display ('permutation test')
```

```
[p1, observeddifference1, effectsize1] = permutationTest(avg_oats, avg_SW, 10000, 'plotresult', 1)
[p2, observeddifference2, effectsize2] = permutationTest(avg_oats, avg_barley, 10000, 'plotresult', 1)
[p3, observeddifference3, effectsize3] = permutationTest(avg_oats, avg_SB, 10000, 'plotresult', 1)
[p4, observeddifference4, effectsize4] = permutationTest(avg_oats, avg_ley, 10000, 'plotresult', 1)
[p5, observeddifference5, effectsize5] = permutationTest(avg_SW, avg_barley, 10000, 'plotresult', 1)
[p6, observeddifference6, effectsize6] = permutationTest(avg_SW, avg_SB, 10000, 'plotresult', 1)
[p7, observeddifference7, effectsize7] = permutationTest(avg_SW, avg_ley, 10000, 'plotresult', 1)
[p8, observeddifference8, effectsize8] = permutationTest(avg_barley, avg_SB, 10000, 'plotresult', 1)
[p9, observeddifference9, effectsize9] = permutationTest(avg_barley, avg_ley, 10000, 'plotresult', 1)
[p10, observeddifference10, effectsize10] = permutationTest(avg_SB, avg_ley, 10000, 'plotresult', 1)
[p11, observeddifference11, effectsize11] = permutationTest(avg_TA, avg_BS, 10000, 'plotresult', 1)
```

```
Significance_crops = [p1 p2 p3 p4 p5 p6 p7 p8 p9 p10]';
```

```
Effect_crops = [effectsize1 effectsize2 effectsize3 effectsize4 effectsize5 effectsize6 effectsize7
effectsize8 effectsize9 effectsize10]';
```

```
Observed_crops = [observeddifference1 observeddifference2 observeddifference3
observeddifference4 observeddifference5 observeddifference6 observeddifference7
observeddifference8 observeddifference9 observeddifference10]';
```

```
% RMSE:
```

```
RMSE1 = sqrt(nanmean((avg_oats-avg_SW).^2));
RMSE2 = sqrt(nanmean((avg_oats-avg_barley).^2));
RMSE3 = sqrt(nanmean((avg_oats-avg_SB).^2));
RMSE4 = sqrt(nanmean((avg_oats-avg_ley).^2));
RMSE5 = sqrt(nanmean((avg_SW-avg_barley).^2));
RMSE6 = sqrt(nanmean((avg_SW-avg_SB).^2));
RMSE7 = sqrt(nanmean((avg_SW-avg_ley).^2));
RMSE8 = sqrt(nanmean((avg_barley-avg_SB).^2));
RMSE9 = sqrt(nanmean((avg_barley-avg_ley).^2));
RMSE10 = sqrt(nanmean((avg_SB-avg_ley).^2));
RMSE11 = sqrt(nanmean((avg_TA-avg_BS).^2));
```

```
RMSE_crops = [RMSE1 RMSE2 RMSE3 RMSE4 RMSE5 RMSE6 RMSE7 RMSE8 RMSE9
RMSE10]';
```

```
% Mean value:
```

```
mean_oats = nanmean(avg_oats);
mean_SW = nanmean(avg_SW);
mean_barley = nanmean(avg_barley);
```

```

mean_SB = nanmean(avg_SB);
mean_ley = nanmean(avg_ley);
mean_BS = mean(avg_BS);
mean_TA = mean(avg_TA);

mean_crops = [mean_oats mean_SW mean_barley mean_SB mean_ley]';

% Variance from mean
var_oats = nanvar(avg_oats);
var_SW = nanvar(avg_SW);
var_barley = nanvar(avg_barley);
var_SB = nanvar(avg_SB);
var_ley = nanvar(avg_ley);
var_BS = nanvar(avg_BS);
var_TA = nanvar(avg_TA);

var_crops = [var_oats var_SW var_barley var_SB var_ley]';

% Comparing the albedo for each year:
Crops_2017 = avg_TA(1:365);
Crops_2018 = avg_TA(366:730);
Crops_2019 = avg_TA(731:1095);
Crops_2020 = avg_TA(1096:end);

[p12, observeddifference12, effectsize12] = permutationTest(Crops_2017, Crops_2018, 10000,
'plotresult', 1)
[p13, observeddifference13, effectsize13] = permutationTest(Crops_2017, Crops_2019, 10000,
'plotresult', 1)
[p14, observeddifference14, effectsize14] = permutationTest(Crops_2017, Crops_2020, 10000,
'plotresult', 1)
[p15, observeddifference15, effectsize15] = permutationTest(Crops_2018, Crops_2019, 10000,
'plotresult', 1)
[p16, observeddifference16, effectsize16] = permutationTest(Crops_2018, Crops_2020, 10000,
'plotresult', 1)
[p17, observeddifference17, effectsize17] = permutationTest(Crops_2019, Crops_2020, 10000,
'plotresult', 1)

Significance_years = [p12 p13 p14 p15 p16 p17]';
Effect_years = [effectsize12 effectsize13 effectsize14 effectsize15 effectsize16 effectsize17]';
Observed_years = [observeddifference12 observeddifference13 observeddifference14
observeddifference15 observeddifference16 observeddifference17]';

RMSE12 = sqrt(nanmean((Crops_2017-Crops_2018).^2));
RMSE13 = sqrt(nanmean((Crops_2017-Crops_2019).^2));

```

```

RMSE14 = sqrt(nanmean((Crops_2017-Crops_2020).^2));
RMSE15 = sqrt(nanmean((Crops_2018-Crops_2019).^2));
RMSE16 = sqrt(nanmean((Crops_2018-Crops_2020).^2));
RMSE17 = sqrt(nanmean((Crops_2019-Crops_2020).^2));

RMSE_years = [RMSE12 RMSE13 RMSE14 RMSE15 RMSE16 RMSE17]';

var_2017 = nanvar(Crops_2017);
var_2018 = nanvar(Crops_2018);
var_2019 = nanvar(Crops_2019);
var_2020 = nanvar(Crops_2020);

var_years = [var_2017 var_2018 var_2019 var_2020]';

mean_2017 = nanmean(Crops_2017);
mean_2018 = nanmean(Crops_2018);
mean_2019 = nanmean(Crops_2019);
mean_2020 = nanmean(Crops_2020);
mean_2017 = nanmean(Crops_2017);

mean_years = [mean_2017 mean_2018 mean_2019 mean_2020]';

[M_2017,I_2017] = max(Crops_2017);
[M_2018,I_2018] = max(Crops_2018);
[M_2019,I_2019] = max(Crops_2019);
[M_2020,I_2020] = max(Crops_2020);

[M_BS17,I_BS17] = max(avg_BS(1:365));
[M_BS18,I_BS18] = max(avg_BS(366:730));
[M_BS19,I_BS19] = max(avg_BS(731:1095));
[M_BS20,I_BS20] = max(avg_BS(1096:end));

%% Figure production
% Creates figures for the comparison between crops, the total crops vs bare soil and the area of the
crops.
% The figures are then saved to the selected output folder.

figure(1)
hold on
title('Crops albedo time series')
xlabel('Year')
ylabel('Albedo')
set(gca,'xcolor','k')
set(gca,'ycolor','k')

```

```

set(gcf,'color','w')
ylim([0.07 0.25])
plot(avg_oats,'-', 'LineWidth',2,'Color','#c92112')
plot(avg_SW,'-', 'LineWidth',2,'Color','#1d14c9')
plot(avg_barley,'-', 'LineWidth',2,'Color','#1dab37')
plot(avg_SB,'-', 'LineWidth',2,'Color','#000000')
plot(avg_ley,'-', 'LineWidth',2,'Color','#d117bf')
legend('Oats','Spring Wheat','Barley','Sugar beets','Ley','location','northeast')
hold off
temp = [outputfolder,filesep,'All_crops_albedo',num2str(i),'.tif'];
saveas(gcf,temp);

```

figure(2)

```

hold on
title('Total crops vs bare soil time series')
xlabel('Year')
ylabel('Albedo')
set(gca,'xcolor','k')
set(gca,'ycolor','k')
set(gcf,'color','w')
plot(avg_BS,'-', 'LineWidth',2,'Color','#f52a4f')
plot(avg_TA,'-', 'LineWidth',2,'Color','#4287f5')
legend('Bare soil','Total albedo of crops')
hold off
temp = [outputfolder,filesep,'All_crops_absorbed',num2str(i),'.tif'];
saveas(gcf,temp);

```

figure(3)

```

hold on
title('Area of the crops and bare soil')
xlabel('Year')
ylabel('Ha')
set(gca,'xcolor','k')
set(gca,'ycolor','k')
set(gcf,'color','w')
bar(Ha_crops,'stacked')
legend('Oats','Spring Wheat','Barley','Sugar beets','Ley','Bare soil')
hold off
temp = [outputfolder,filesep,'Ha_barchart',num2str(i),'.tif'];
saveas(gcf,temp);

```

```

%% MODIS validation

% Script developed by Victor Andréasson 2022-2023
% credits: Zhanzhang Cai & Joanna Eaton

% Compares the albedo calculations made on the sentinel 2 (S2) data with
% the premade MODIS calculated albedo.

%% Decides a folder for all the outputs and settings for running the script

clear
close all

% Folder where all output will be saved:
outputfolder = ['T:\Ex-jobb_VictorAndréasson\Results'];

% Years that will be processed:
yr = 2017:2020;

%% MODIS preparation:
% WSA = White-sky albedo
% BSA = Black-sky albedo

WSA_MODIS = readmatrix(['T:\Ex-
jobb_VictorAndréasson\data\MODIS_WSA_TIMESAT_smooth.csv']);
WSA_MODIS = cast(WSA_MODIS,'double');
WSA_MODIS(WSA_MODIS == -9999) = nan;
WSA_MODIS = WSA_MODIS * 0.001;

BSA_MODIS = readmatrix(['T:\Ex-
jobb_VictorAndréasson\data\MODIS_BSA_TIMESAT_smooth.csv']);
BSA_MODIS = cast(BSA_MODIS,'double');
BSA_MODIS(BSA_MODIS == -9999) = nan;
BSA_MODIS = BSA_MODIS * 0.001;

for i = yr
    i
    files_S2 = dir(['T:\Ex-
jobb_VictorAndréasson\data\daily_albedo_sub\daily_albedo_sub\albedo_',num2str(i),'*.tif']);

    for ii = 1:length(files_S2)
        ii
        S2 = geotiffread(fullfile(files_S2(ii).folder,files_S2(ii).name));
        S2 = cast(S2,'double');
        S2(S2 == -9999) = nan;
        S2 = S2 / 10000;          % Divides the TOA reflectance to get surface albedo.
        S2 = S2(245:295,485:535); % Modifying S2 to fit with the MODIS data.
    end
end

```

```

% Creates a year matrix and a day of year matrix:
y = i;
doy = str2double(files_S2(ii).name(end-6:end-4));
t{i-yr(1)+1}(ii) = datetime(datestr(datenum(y,1,1)+doy-1));

% Saves S2 values in a string divided by years
mean_S2{i-yr(1)+1}(ii) = nanmean(S2(:));
medi_S2{i-yr(1)+1}(ii) = nanmedian(S2(:));
end
end

%% Statistical testing
% Runs a permutation test (must have the permutationTest.m function in the
% same folder. This outputs a P-value, the observed difference and an
% effect size based on Hedges'g.
%
% RMSE is also calculated for the differences between the crops as well as
% variance and mean value for the individual crops.

Sentinel2 = cell2mat(medi_S2);

RMSE_W = sqrt(nanmean((Sentinel2-WSA_MODIS).^2));
mdl = fitlm(Sentinel2,WSA_MODIS');
mdl.Rsquared.Ordinary

RMSE_B = sqrt(nanmean((Sentinel2-BSA_MODIS).^2));
md2 = fitlm(Sentinel2,BSA_MODIS');
md2.Rsquared.Ordinary

[p, observeddifference, effectsize] = permutationTest(Sentinel2, WSA_MODIS, 10000, 'plotresult', 1)
[p1, observeddifference1, effectsize1] = permutationTest(Sentinel2, BSA_MODIS, 10000, 'plotresult',
1)

R_W = corrcoef(Sentinel2,WSA_MODIS);
R_B = corrcoef(Sentinel2,BSA_MODIS);

mean_S2 = nanmean(Sentinel2);
mean_WSA_MODIS = nanmean(WSA_MODIS);
mean_BSA_MODIS = nanmean(BSA_MODIS);

var_S2 = nanvar(Sentinel2);
var_WSA_MODIS = nanvar(WSA_MODIS);
var_BSA_MODIS = nanvar(BSA_MODIS);

figure(1)

```

```
hold on
title('Comparison of albedo data from Sentinel-2 and MODIS')
xlabel('Years')
ylabel('Albedo')
set(gca,'xcolor','k')
set(gca,'ycolor','k')
set(gcf,'color','w')
ylim([0 0.3])
```

```
plot(Sentinel2,'-', 'LineWidth',2,'Color','#0066ff')
plot(WSA_MODIS,'-', 'LineWidth',2,'Color','#ff9900')
```

```
legend('Sentinel-2','WSA-MODIS')
hold off
temp = [outputfolder,filesep,'Comparison_MODIS.tif'];
saveas(gcf,temp);
```

```
figure(2)
hold on
title('Comparison of albedo data from Sentinel-2 and MODIS')
xlabel('Years')
ylabel('Albedo')
set(gca,'xcolor','k')
set(gca,'ycolor','k')
set(gcf,'color','w')
ylim([0 0.3])
```

```
plot(Sentinel2,'-', 'LineWidth',2,'Color','#0066ff')
plot(BSA_MODIS,'-', 'LineWidth',2,'Color','#ab0af0')
```

```
legend('Sentinel-2','BSA-MODIS')
hold off
temp = [outputfolder,filesep,'Comparison_MODIS.tif'];
saveas(gcf,temp);
```

```
figure(3)
hold on
title('Comparison of albedo data from Sentinel-2 and MODIS')
xlabel('Years')
ylabel('Albedo')
set(gca,'xcolor','k')
set(gca,'ycolor','k')
set(gcf,'color','w')
ylim([0 0.3])
```

```
plot(Sentinel2,'-', 'LineWidth',2,'Color','#0066ff')
plot(WSA_MODIS,'-', 'LineWidth',2,'Color','#ff9900')
```



```
plot(BSA_MODIS,'-', 'LineWidth',2, 'Color', '#ab0af0')  
  
legend('Sentinel-2', 'WSA-MODIS', 'BSA-MODIS')  
hold off  
temp = [outputfolder, filesep, 'Comparison_MODIS.tif'];  
saveas(gcf, temp);
```