remote sensing

Article

How did Heat Wave in 2018 Influence Agricultural Vegetation in Demmin?

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Abstract: In 2018, Germany experienced the warmest spring and summer seasons since 1881. The impacts of the heat wave cannot be ignored. This study tries to detect the change in the growth of agricultural vegetation and the change in the variation pattern of temperature in 2018. The study is based on open-source satellite data and atomospheric reanalysis data. The results show that NDVI and LAI variation patterns changed in 2018. The green period of the vegetation appears to be shorter than in 2017. The longer and consistant warm season in 2018 is also illustrated by the daily temperature plots. The early temperature rise in April and consistant high temperature are observed as the patterns that might help in drought forecast and monitoring systems.

Keywords: heat wave; drought; NDVI; LAI

1. Introduction

In 2018, Germany experienced the warmest spring and summer seasons since 1881. According to the report of "drought & heat wave summer 2018 (Germany)" (Mühr *et al.* 2018), the heat wave period lasted 17 days from Jul 24 to Aug 9 and the highest temperature reached 39.5 °C. The four-month period from April to July also exceeded the normal average temperature by 2.8 °C. As the consequence, a drought longer than two months started from mid-June. About 90% of German territory were influenced by the heat wave and drought in 2018.

As one of the major envionmental disasters, drought is always a big topic in agriculture. From the study of indices (Morid *et al.* 2006; Ghulam *et al.* 2007) to the yiled estimation models(Unganai & Kogan 1998; Anderson *et al.* 2016), scientists have put much emphasis on the percipitation and soil moisture. This paper is focused on temperature as an environmental indicator and the change in the growth of agricultural vegetation during heat wave.

The status of agricultural vegetation could be to certain extent seen by NDVI (Normalized Difference Vegetation Index) and LAI (Leaf Area Index). So the change in vegetation growth could be observed by the change in the variation patterns of the indices.

In order to answer the question in the title, this paper tries to answer the following sub-questions:

- Did the variation pattern of NDVI and LAI change? And how?
- Did the variation pattern of temperature change? And how?
- How are these two changes related?

2. Materials and Methods

Compared to traditional drought monitoring methods that require huge amounts of in-situ data, the modern drought monitoring systems are to a large extent based on satellite data (Thenkabail 2015). The sufficency of satellite data is increasing, as more and more satellite missions are lauched and will be launched in the future. Nowadays, many satellite data hubs are open to the public, from which the whole scientific community can benefit .Satellite data help us to develop more comprehensive methods and models (AghaKouchak *et al.* 2015). Challenges should also be considered, e.g. data continuity. The methods of this paper are based on open-source satellite data. Some simplifications are made due to time restriction and data availability.

First of all, a group of agricultural fields in Alt Tellin, Demmin, Germany is selected as the study area (shown in Figure 1). The 2nd level products of Landsat 8 that cover this area are downloaded from USGS Earth Explorer (https://earthexplorer.usgs.gov). Data of year 2017 and 2018 during the time period from April to early September are aquired. After a manual check, images with more than 50% clouds coverage in study area are eliminated. Five images of each year are eventually selected that can be matched in pairs (shown in table 1). The images are cropped into the extent of study area. Six sample points are also selected based on the non-cloud areas (also shown in Figure 1).

Table 1. Image Acquisition Dates

Time Slot[1]	2017	2018
1	Apr 6	Apr 9
2	May 1	May 4
3	Jun 2	May 20
4	Jun 9	Jun 28
5	Aug 28	Sep 9

[1] Available satellite images (with less cloud coverage) of the two years are matched into pairs according to acquisition dates. The dates of the same time slot are selected as close as possible.

Figure 1. Study area and sample points in Demmin, Germany. Points are numbered according to their order in the attibute table.

Secondly, NDVI and LAI are calculated for this whole area on the selected dates (images). The indices of six sample points are then extracted and plotted. A change in the index variation patterns can thus be observed.

The calculation of NDVI is as follows:

$$NDVI = (NIR - Red)/(NIR + Red) \tag{1}$$

NIR – near infrared band reflectance;
Red – red band reflectance

The estimation of LAI based on NDVI follows the method developed by Saito et al (Saito *et al.* 2001):

$$LAI = 0.5 * e^{(2.33 * NDVI)} \tag{2}$$

Next, the daily spatial temperature data from April to August in both years are downloaded from ECMWF database (https://www.ecmwf.int). The maximum temperature since previous post-processing at 1 pm is selected to get a possibly higher temperature during the day. The data are developed by ERA-Interim atomospheric reanalysis model and fit to the temperature at 2 meters above ground. Due to the spatial resolution, the temperature values that can be acquired in the whole study area are the same. So only one sample point is used to extract the temperature data. The temperature data are then plotted to get an overview of the temperature changes in the study time periods.

Finally, all the plots are compared. Certain patterns are found separately in NDVI/LAI variation and temperature variation.

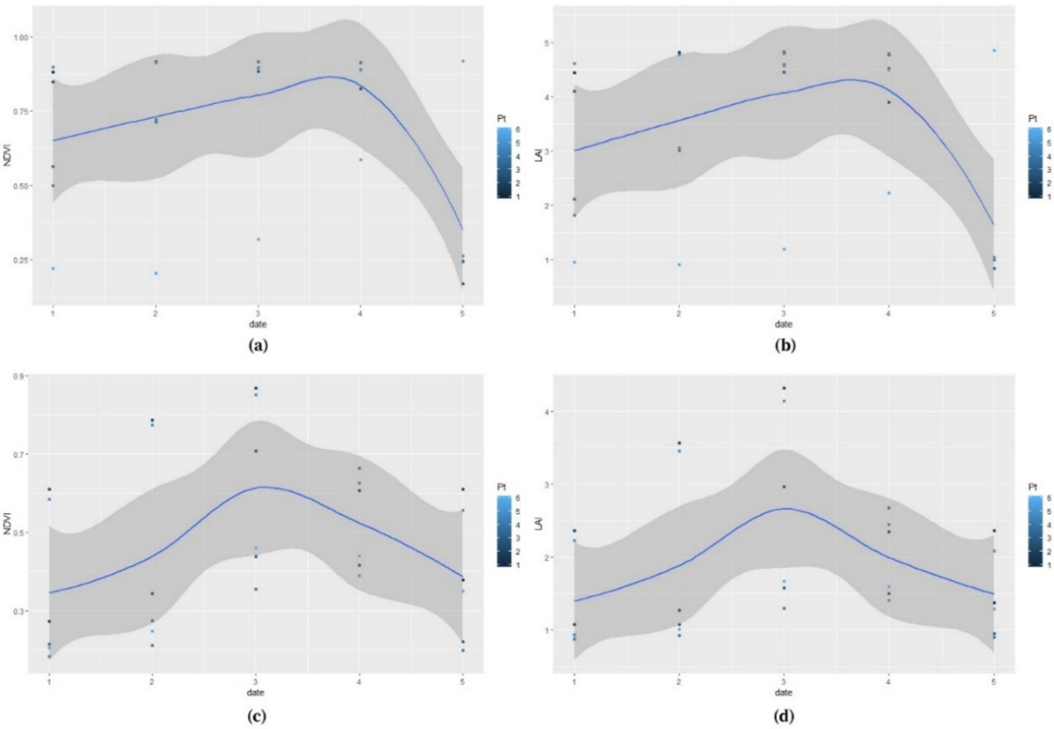
All calculation are done with R (R Core Team 2019) and R Studio as an integrated development environment (R Studio Team 2019). The following packages are used: raster(Hijmans 2019), rgdal(Bivand *et al.* 2019) and RStoolbox(Leutner *et al.* 2019).

Figures and plots are developed in R Studio with ggplot2 package(Wickham 2016) and in QGIS 3.6.1 (QGIS Development Team 2019).

3. Results

3.1. NDVI & LAI patterns

NDVI and LAI values are plotted for the five time slots (see Table 1). As shown in Figure 2, both NDVI and LAI values are generally higher in 2017. In 2017, the indices gradually rise from early April until the peak values in mid-June (time slot 4). Then they drop to a low value because of the harvest. In 2018, the indices are much lower in April and early May before they reach the peak values in late May (time slot 3) and then start to drop already in June (time slot 4). The change in the variation patterns is significant.



(a) (b) (c) (d)

Figure 2. NDVI & LAI variations in both years: (**a**) NDVI variation in 2017; (**b**) LAI variation in 2017; (**c**) NDVI variation in 2018; (**d**) LAI variation in 2018.

3.2. Temperature variation

Daily temperature data are plotted from April to August in both years as shown in Figure 3. Compared to 2017, temperature in 2018 begins to rise early in April. The temperature also fluctuates less in 2018 and remains at high values during the whole period.

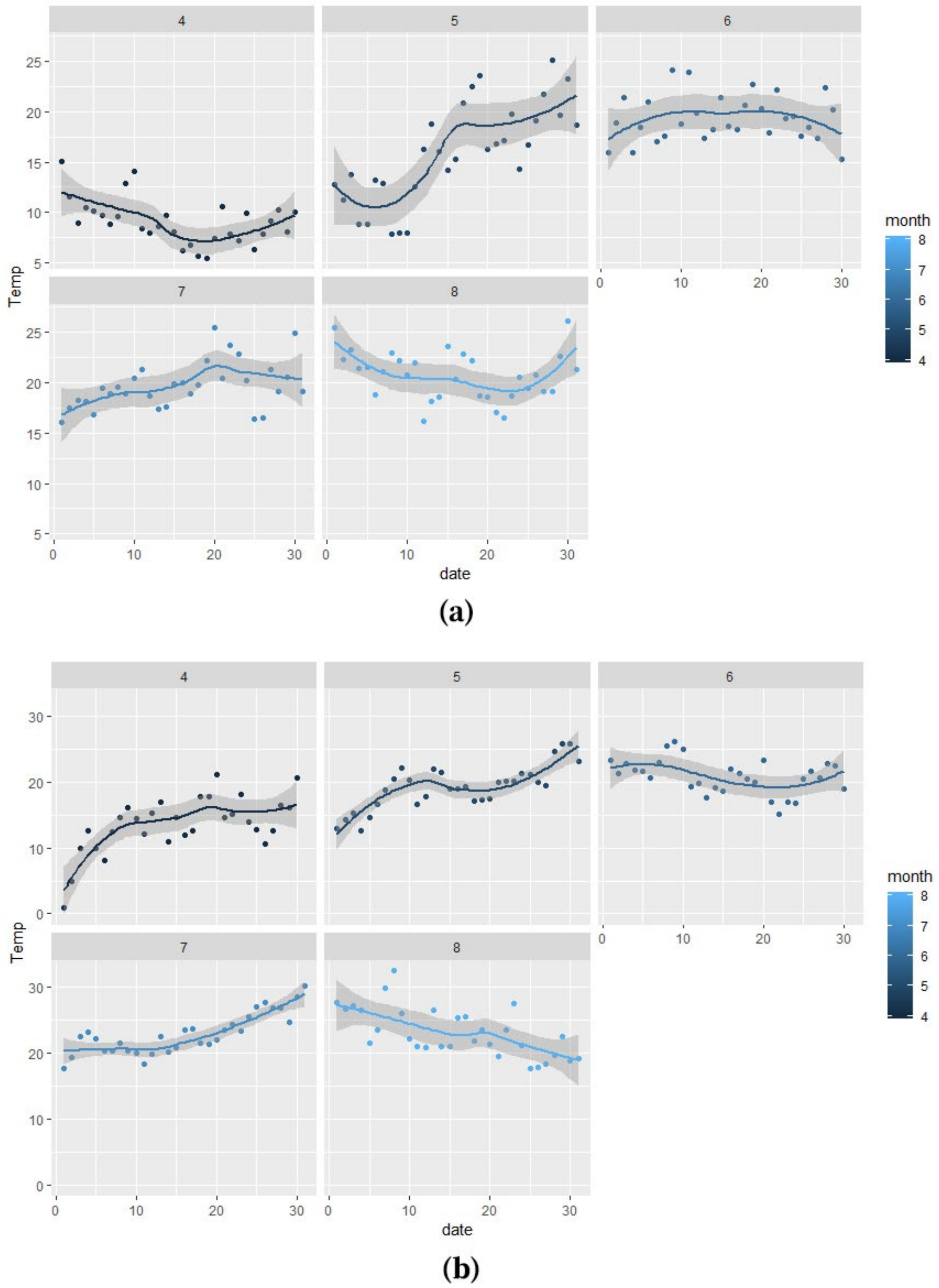


Figure 3. Temperature variations in both years from April to August: (**a**) in 2017; (**b**) in 2018.

4. Discussion

Five of the six sample points in 2017 follow the similar NDVI and LAI variation patterns while point 6 appears different (Figure 2a&b). The reason that point 6 has a different variation requires more research. It might be a change in the vegetation type or human interference. In this study, this point is no longer considered.

All six points in 2018 follow the similar pattern, which has a steeper peak than in 2017 (Figure 2c&d). The peak is also lower in value than in 2017. A conclusion could be drawn that the vegetation in this area grows better and has a longer green period in 2017 than in 2018.

The temperature plots show that there's a longer and consistant warm period in 2018 (Figure 3a&b), which is highly possible to be a reason for the green period decrease in 2018. The temperature begins to rise early in April in 2018, which might possibly hinder the vegetation growth. The consistant high temperature with less fluctuation might also lead to an early decline of the indices in June. These patterns could be taken into account in the drought forecast and monitoring systems.

Future research might integrate in-situ data with satellite data to get a better view of the change in the vegetation growth. The crop production data could also be compared to confirm the result of such change in the index variation patterns. Furthermore, other environmental indicators, such as percipitaion, might also be conbined with temperature to illustrate the weather change.

5. Conclusions

The variation pattern of NDVI/LAI changed in 2018, with steeper rise and decline. A worse vegetation growth with shortened green period could be indicated.

The variation pattern of temperature also changed, with early warm season and consistant hot days in summer. These patterns might explain the reason that vegetation growth is hindered in April. After a short green period, a drough could happen after the consistant heat.

To sum up, the impact of heat wave in 2018 could be illustrated by the significant change in variation patterns of NDVI and LAI. This change could be possibly explained by the change in temperature variation patterns. Thus, detection of these patterns might be useful in drought forecast and monitoring systems.

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