https://doi.org/10.5194/egusphere-2024-1872
Preprint. Discussion started: 4 July 2024

Earth observation reveals reduced winter wheat growth and the importance of soil water storing capacity during drought

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Abstract. Drought poses increasing challenges to global food production. Knowledge about the influence of drought on crop development and about the role of soil properties in drought risk analysis and mitigating drought impacts at the landscape level is important to guide climate change adaptation. Satellite earth observations can provide area-wide insights into crop growth processes that may help identify risk factors and quantify vulnerability to drought. Here, we evaluate the potential of Sentinel-2 to reveal interactions of plant-growth and soil parameters during variable weather conditions. As a case study, we assess winter wheat growth on 13 fields belonging to commercial farmers in southern Sweden in a dry year and a year with normal weather conditions. To track crop growth, green leaf area index (GLAI) was estimated from satellite imagery using a radiative transfer model. Proxies for winter wheat growth rate, peak GLAI, and the timing of peak GLAI were derived from the GLAI development at the single field level.

We then compared the crop growth proxies between the two years and across the fields and related them to measured soil properties. We found a lower growth rate, lower peak GLAI and earlier peak GLAI in the dry year compared to the year with normal weather conditions. An increase in peak GLAI in the dry year was also shown to be related to a higher growth rate, and this was not shown in the year with normal precipitation. Differences in crop development between years were large for some fields but small for other fields: suggesting that soil properties play a role in crop response to drought. We found that fields with a higher amount of plant available water capacity had better crop performance in the dry year and smaller relative differences in growth rate between the two years. The observed lower growth rate, lower peak GLAI, and earlier peak in the dry year compared to the year with normal weather conditions, demonstrate that satellite imagery can be used to quantify plant-soil-weather interactions at scales relevant to commercial farming. Our investigation serves as a first step towards supporting drought risk management, drought adaptation and communication activities on this important topic.

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1 Introduction

Extreme weather events such as droughts have become more frequent and severe in recent years due to climate change, posing challenges to global food and feed production (IPCC 2022). Drought is one of the main climatic constraints limiting crop growth and crop productivity (Fahad et al. 2017; Matiu et al. 2017; Ru et al. 2023). Water is crucial for plant growth, and plants can respond to water limitation through different mechanisms, such as reducing water losses through transpiration by closing their stomata (Huang et al. 2020) or by reducing leaf area (Wasaya et al. 2023). In turn, the photosynthesis rate and thus carbon acquisition decrease. Plants may also accelerate their development to complete the plant life cycle before the occurrence of a severe water deficit (Abid et al. 2018; Seleiman et al. 2021). The impact of drought on crops is complex and depends on several factors including the plant species and variety, the developmental stage of plants, the timing, duration and severity of the drought (Gray and Brady 2016), as well as the properties of the soil (Bodner et al. 2015).

The capacity of soil to sustain plant growth and crop productivity is affected by biological, chemical and physical soil properties, which collectively determine the soil conditions for plant growth (Stockdale et al. 2002). Soils with higher resilience to drought allow water to infiltrate and can store moisture to sustain plant growth (Rockström 2003; Bodner et al. 2015). Higher moisture in the soil may also benefit nutrient uptake during drought. A water deficit could lead to a lack of nutrients in crops as nutrients are mainly transported into plants through water uptake (He and Dijkstra 2014). Plant roots must also be able to penetrate the soil to access water and nutrient resources, where a high penetration resistance, which increases with dry conditions, could impede root growth (Bengough et al. 2011; Colombi et al. 2018). Recent research also shows evidence that certain rhizosphere microbiomes might enhance plant growth during dry conditions (Rolli et al. 2015; Rubin et al. 2017; de Vries et al. 2020). Therefore, the soil properties are of high importance to sustain crop growth during drought.

Plant growth dynamics can be quantified with ecophysiological properties such as the green leaf area index (GLAI), which is the ratio of photosynthetically active leaf area to ground area (Watson 1947). Previous studies demonstrated that the influence of soil properties and soil-borne stress on plant growth can be detected using GLAI. For example, positive relationships between GLAI and soil water content have been found (Chen et al. 2021), and GLAI at the heading stage of winter wheat has been shown to decrease with a high degree of soil compaction (Lipiec et al. 1991) in field experiments. The growth rate estimated from GLAI has also been shown to be related to soil carbon and nitrogen contents (Hirooka et al. 2017). However, there is still limited information about how soil properties affect crop development under various weather conditions, especially at scales relevant to commercial agriculture (i.e., at the landscape scale). Research at larger scales than field experiments is particularly important since the heterogeneity of environmental factors in the landscape is more complex than what can be investigated in typical field plot experiments.

Monitoring crop growth at the landscape scale can be done with satellite remote sensing, for example using the twin constellation of Sentinel-2A and 2B. The Sentinel satellites provide a high spatial resolution optical imagery of up to 10 metres, and a high revisit time of one to four days depending on the latitude (Drusch et al. 2012). The Sentinel-2 multispectral sensors have been shown to be suitable for estimating GLAI for different crop species (Clevers et al. 2017; Revill et al. 2019; Dong et

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al. 2020; Ali et al. 2021). One promising way to interpret satellite data for ecophysiological traits is the use of radiative transfer models. Radiative transfer models describe the relationship between leaf and canopy traits and spectral properties of plants using physical principles (Jacquemoud et al. 1996; Myneni et al. 1997; Verhoef 1998). Thus, in contrast to the widely used vegetation indices, there is no need to establish empirical relationships between vegetation indices and crop traits (Atzberger et al. 2011). Those empirical relationships are usually not transferable in space and time, and hence not suitable for studies at the landscape scale. In addition, vegetation indices such as the widely used Normalized Difference Vegetation Index (NDVI) saturate at low biomass levels (Myneni and Williams 1994; Prabhakara et al. 2015), which is undesirable for a reliable and robust quantification of plant growth. The combination of satellite images and radiative transfer models allows estimating GLAI on a large scale.

The use of satellite-derived GLAI for crop growth characterization and productivity has become common in recent years (Punalekar et al. 2018; Peng et al. 2019; Dong et al. 2020; He et al. 2021; Graf et al. 2023), but knowledge about how extreme weather, such as drought, affects GLAI-development remains scarce. The year 2018 was characterised by an unusually dry and hot spring and summer in northern Europe (Wilcke et al. 2020). These extreme conditions had a large impact on agriculture, and around 40% of the cropping areas with winter wheat in Northern Europe had yields below the 10th percentile (Beillouin et al. 2020). The probability of droughts is increasing due to climate change (Wilcke et al. 2020), posing increasing challenges to crop production. Studying the impact of drought on plant growth and development, and the role of soil properties in aggravating or mitigating drought impacts, can provide crucial knowledge for future climate change adaptations. In the present study, the aims were to:

i) analyse winter wheat development in farm fields within a region in southern Sweden by quantifying GLAI based on Sentinel-2 data,

ii) investigate the impact of drought on winter wheat GLAI development by comparing a dry year (year 2018) and a year with normal weather conditions (year 2021), and

iii) examine the influence of soil properties on differences between GLAI development across fields and between the two years.

2 Materials and Methods

2.1 Study area and meteorological data

The study area was located in the south of Sweden at a latitude of approximately 58.5°, spanning 160 km from the west to the east (Fig. 1), and is characterized by a humid continental climate (Peel et al. 2007). Winter wheat is the major crop cultivated in Sweden in general and in the study area (Sjulgård et al. 2022). We included 13 fields in this study, belonging to commercial farmers that were cultivated with winter wheat (Triticum aestivum L.) in both 2018 and 2021, and for which detailed soil data were available. The centroid coordinates of the fields were used to obtain the daily temperature and precipitation data for each field. The meteorological data were obtained from the PTHBV database, available from the Swedish Meteorological and

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Hydrological Institute (SMHI). The data include gridded and interpolated daily mean temperature and precipitation at a resolution of 4 km by 4 km (SMHI 2023). The interpolation is based on 700 meteorological stations across Sweden and orographic effects (Berg et al. 2015). Differences in weather conditions between fields and years were assessed by the De Martonne Aridity Index (DMI; De Martonne 1926)), defined as:

$$DMI = \frac{P_m}{T_m+10} \quad (1)$$

where Pm is the monthly total precipitation (mm) and Tm is the monthly average temperature (°C). A higher DMI indicates wetter conditions, while a lower DMI value indicates drier conditions. In the summer 2018, the DMI was on average 1.2 mm/°C (SD = 0.06) per month for the 13 fields, which was drier than the long-term average between 1991 and 2020 of 2.9 mm/°C (SD = 0.19; Fig. S1). In 2021, the DMI was closer to the long-term average with a mean during the summer of 3.2 mm/°C (SD = 0.16), and with similar values between the fields.

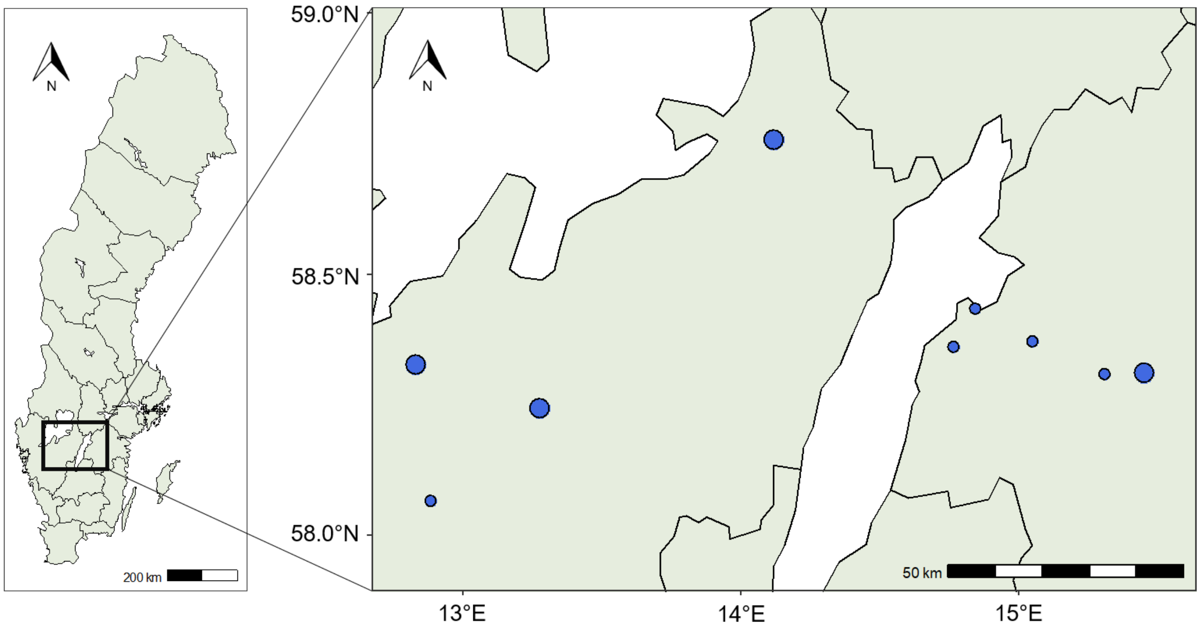

Fig. 1. A map of Sweden with county borders showing the location of the study area (left), and the map displaying the locations of the fields (right). A small blue circle indicates the location of one field, and a larger blue circle indicates two fields close to each other.

2.2 GLAI derived from satellite data

The twin constellations of the Sentinel-2A and B satellites have a revisit time of two days in the study area. Downloading and processing of Sentinel-2 data were performed using the open-source Python Earth Observation Data Analysis Library (EOdal, Graf et al. 2022). The Sentinel-2 scenes were obtained for the years 2018 and 2021 from Microsoft Planetary Computer. 20 m

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and 10 m bands were obtained, and the Sentinel-2 scenes and 20 m bands were resampled to 10 m using nearest-neighbour interpolation to generate equal spatial resolution. The Sentinel-2 scenes were cropped to only retain pixels within the 13 fields based on a shapefile containing the field boundaries. From the resampled scene classification layer, only pixels from the scene classification layer class 4 (vegetation) and class 5 (bare soil) were kept to filter out pixels containing clouds, snow, shadow, and dark areas. Further filtering was performed to remove dates with a cloud cover of ≥ 10% on a field-per-field basis.

The GLAI was derived from the radiative transfer model PROSAIL following the approach described in Graf et al. (2023). A lookup table consisting of 50,000 spectra was generated by running the PROSAIL model in forward mode for each Sentinel-2 scene. We randomly generated combinations of leaf and canopy parameters according to a uniform or Gaussian distribution (Table S1). View and illumination geometry were set to scene-specific values extracted from the Sentinel-2 scene metadata. Building on the workflow of Graf et al. (2023), known empirical relationships between GLAI and chlorophyll a and b, and GLAI and the carotenoid content of leaves were used to increase the physiological plausibility of the input parameter combinations. For GLAI retrieval, we compared the Sentinel-2 pixel spectra with the PROSAIL simulated spectra using the mean absolute error as a cost function. We then used the median of the 5000 (10%) best matching simulated spectra in terms of the smallest mean absolute error to derive a GLAI value per Sentinel-2 pixel.

For each Sentinel-2 scene, an average value of GLAI was calculated per field. A smoothed curve was fitted to the GLAI time series by the locally estimated scatterplot smoothing (LOESS) method with a span of 0.3 (Fig. 2). The smoothed curve was also used to identify and remove outliers that were missed by the scene classification layer and the cloud filtering (Fig. S2).

2.3 Crop growth curve parametrisation

The air temperature sum (TSUM) at the location of each field was assessed by adding up the daily mean temperatures exceeding the threshold value of 0 °C, where growth for winter wheat starts (Porter and Gawith 1999), from the 1st of January following:

$$TSUM = \sum_{i=1}^{j} T_i \times \sigma_i$$

$$\sigma_i = \begin{cases} 0 \; if \; T_i \leq 0\,°C \\ 1 \; if \; T_i > 0\,°C \end{cases} \qquad (2)$$

Where Ti is the daily mean temperature and j is the number of days.

From the GLAI development curve, characteristic properties were calculated to estimate the growth rate, green biomass, and timing of development for each field and year (Fig. 2). GLAI increases early in the season due to leaf production in the vegetative growth phase (Bhattacharya 2019). Growth rate during the vegetative growth phase was estimated from the slope of a linear plateau curve with an endpoint at the start of the upper plateau. The linear plateau model was fitted to the GLAI values with a start at a temperature sum of 200 °C (corresponding to the end of April) when the GLAI started to increase around the beginning of the stem elongation (Chen et al. 2009). The GLAI development curve is typically bell-shaped, with the peak GLAI observed around the heading stage for winter wheat (Feng et al. 2019). The timing of the peak GLAI was assessed from the corresponding temperature sum. The GLAI at the peak indicates the maximum green biomass (Lambert et al. 2018; Skakun et al. 2019) and was assessed from the smoothed GLAI curve.

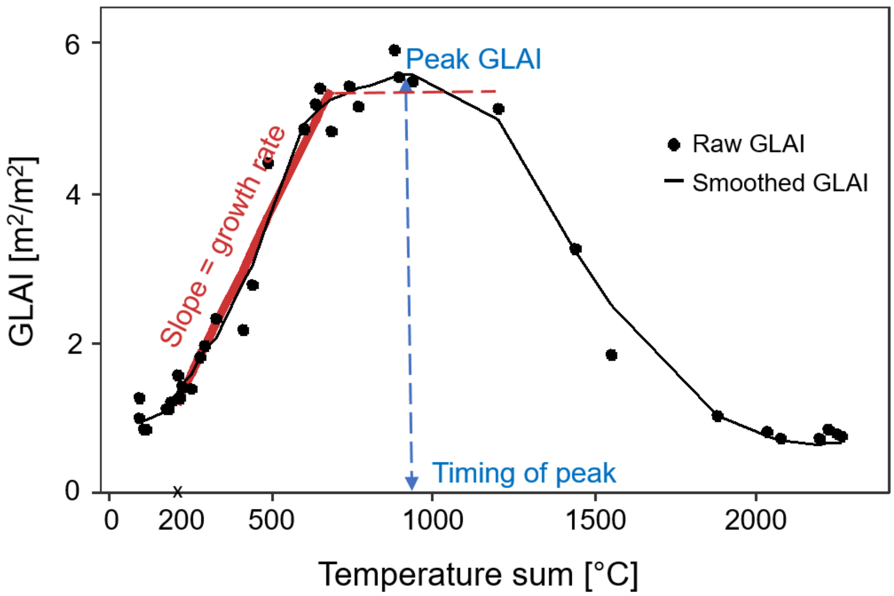

Fig. 2. Example from one of the fields showing the green leaf area index (GLAI) temporal development curve. We obtained proxies for the growth rate from the slope between a temperature sum of 200 °C until the start of the plateau, the peak GLAI from the maximum GLAI, and the timing of peak GLAI from the temperature sum at the peak. The raw GLAI values are shown by black dots and the smoothed GLAI is shown by the black curve.

2.4 Soil sampling and analyses

Soil sampling was conducted in June and in the beginning of July in 2021. Loose soil samples and undisturbed soil cores were collected from the topsoil at five locations in each field. Sampling locations within each field were arranged in a quincunx, with one point in the middle of the field and the others at least a few metres from the field borders. Loose soil samples were taken with a shovel from 0-20 cm depth. The five samples taken in each field were pooled into a plastic bag and the resulting composite sample was air-dried. Five undisturbed soil cores (5 cm in height, 7.2 cm inner diameter) were collected at a depth of 10 cm in each field. The soil core samples were wrapped airtight and stored at 4 °C until further processing.

Soil organic matter content was determined by loss of ignition from the loose soil samples. Cation exchange capacity was analysed using an inductively coupled plasma–optical emission spectrometer (ICP-OES) to obtain the base cations in the soil samples. The base cations and acidity titration were used to calculate the cation exchange capacity at pH 7. Soil water content at the permanent wilting point (-1500 kPa) was determined with pressure plate extractors. Soil water content at field capacity

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was assessed by equilibrating the soil cores to -10 kPa on ceramic plates (ecoTec, Bonn). Plant available water capacity was obtained by calculating the difference in soil water content between field capacity and the permanent wilting point. Dry soil bulk density was determined on the undisturbed soil core samples by drying the samples at 105 °C for 48 h. Soil texture including clay (< 0.002 mm) content was determined from the loose soil samples by sedimentation ('pipette' method).

2.5 Statistical analyses

GLAI development responses to drought were analysed by comparing the differences in crop growth proxies (i.e., growth rate, peak GLAI, and the timing of peak) between the dry year 2018 and the year with normal weather conditions (2021). A two-tailed t-test was applied to determine whether there was a significant difference in growth rate, peak GLAI and the timing of the peak GLAI between the years. Spearman correlation was used to assess the relationships between the crop growth proxies, and between soil properties. To relate soil properties to differences in the growth rate, peak GLAI and the timing of the peak GLAI between the years, the relative difference of the crop growth proxies (ΔGP) between the years 2018 and 2021 was calculated as:

$$\Delta GP = \frac{GP_{2021} - GP_{2018}}{GP_{2018}} \times 100\% \qquad (3)$$

Where GP is the crop growth proxies growth rate, peak GLAI or the timing of the peak GLAI in year 2018 and 2021.
A variance decomposition method proposed by Zuber and Strimmer (2011), called Correlation-Adjusted coRelation (CAR) scores, was used to determine the relative importance of the soil properties for the growth rate, peak GLAI and the timing of the peak GLAI in each year (i.e., for 2021 and 2018), and for the relative difference of the crop growth proxies between the years. CAR scores provide a criterion for variable ranking in linear regression based on the Mahalanobis-decorrelation of covariates (Zuber and Strimmer 2011). The direction of the relationships and p-values were obtained from univariate linear regressions between the crop growth proxies and the soil properties for each year, and for the relative difference of crop growth proxies in 2021 to 2018, respectively. A significance level of $p < 0.05$ was used. The statistical analyses were carried out in R version 4.2.1 (R Core Team 2022) and the CAR scores were calculated from the R package "relaimpo" (Groemping and Lehrkamp 2023).

3 Results

3.1 Growth patterns across years

The differences in crop development between years varied between fields, where certain fields showed a large difference in growth rate, peak GLAI and the timing of the peak GLAI between years, while others showed only small differences (Fig. 3). For growth rate and the peak GLAI, four fields in total had an increase from 2018 to 2021 of less than 10%, while some fields had a difference of 50-59%. The difference between the years in the timing of the peak GLAI was lower in comparison, with

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four fields having an increase <10% and three fields a decrease <10%, while the maximum difference was 30-39% between the years (Fig. 3).

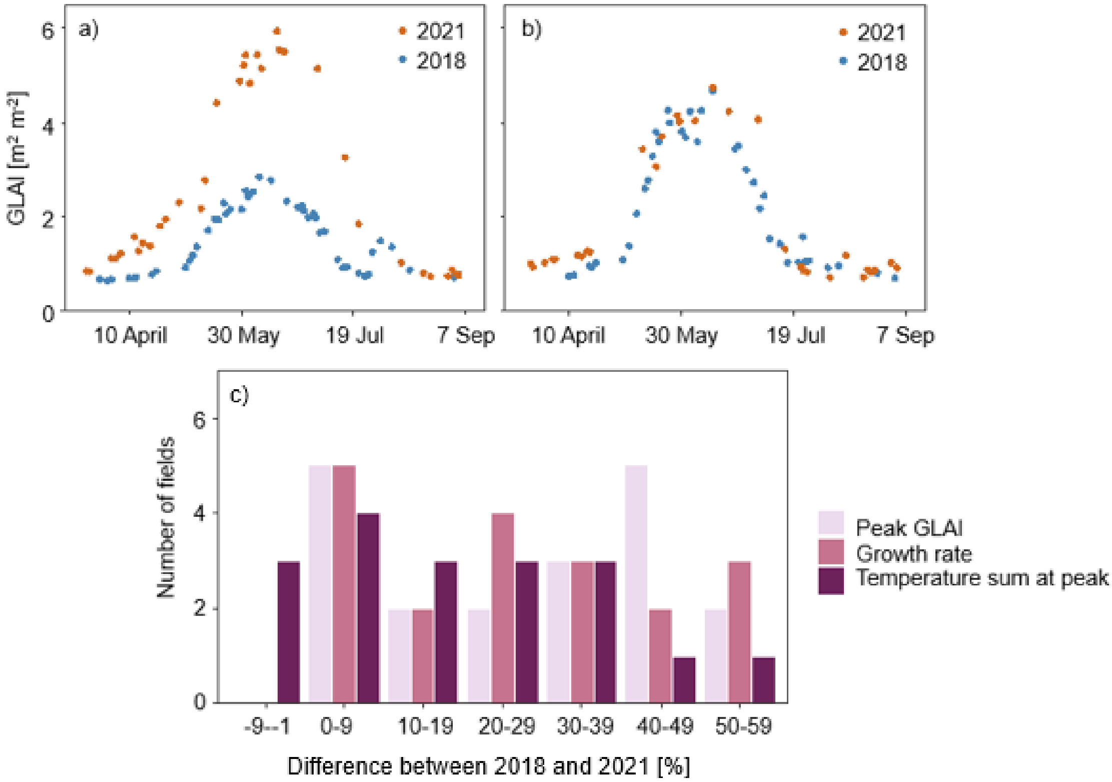

Fig. 3. Temporal evolution of GLAI during 2018 (dry year) and 2021 (year with normal weather conditions) for two different fields with a) a large difference between the years and b) a small difference between the years. c) Number of fields by the percentage difference in the crop growth proxies (i.e., peak GLAI, growth rate and temperature sum at peak GLAI) between the years 2018 (dry year) and 2021 (year with normal weather conditions).

Growth rate was lower during the dry year (2018) compared to the year with normal weather conditions (2021; Fig. 4), indicating reduced plant growth in response to drought. The growth rate during the reproductive period was on average 28% lower in the dry year (2018) than in the year 2021 with closer to normal weather conditions, and we found a significant effect of the year on growth rate ($p < 0.001$; Fig. 4a). The peak GLAI was in general lower during the dry compared to the year with normal weather conditions ($p < 0.001$; Fig. 6c), with an average difference of 40% between the two years. The timing of peak GLAI occurred significantly earlier, i.e. at a lower temperature sum, during the dry year, with the peak GLAI around a temperature sum of 775 °C in the dry year and 881 °C in the year with normal weather conditions ($p = 0.015$; Fig. 4d).

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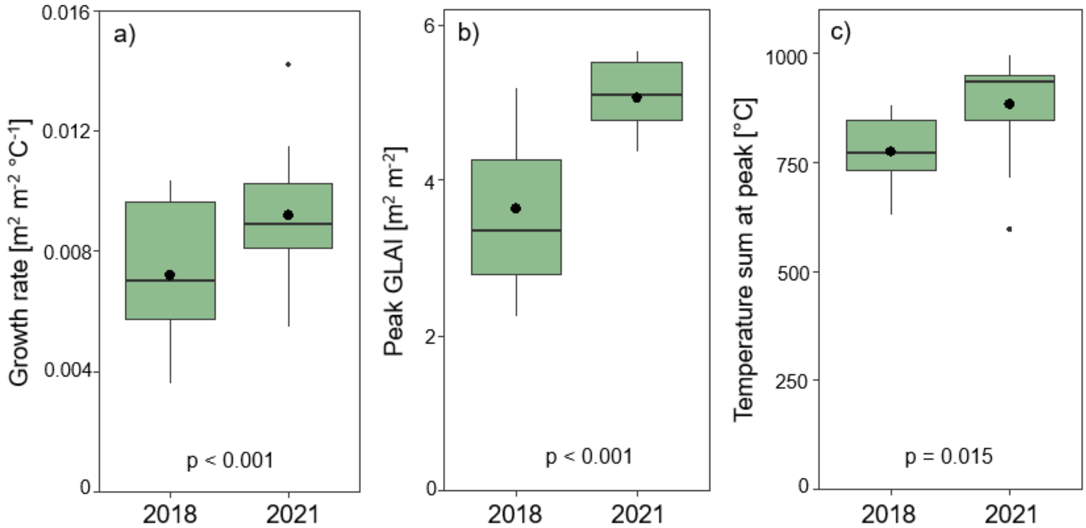

Fig. 4. Crop growth proxies obtained from the temporal evolution of green leaf area index (GLAI) in the dry year 2018 and the year with normal weather conditions 2021; a) growth rate, b) peak GLAI and c) temperature sum at peak GLAI, during the dry year (2018) and the year with normal weather conditions (2021). Data show yearly average (black dots), median, upper and lower quartiles, and minimum and maximum values. P-values from the t-test are displayed for the differences between the years (number of fields, n=13).

The relationships among the different crop growth proxies showed a positive correlation between growth rate and the peak GLAI in the dry year (year 2018), while the relationship was not significant during the year with normal weather conditions. The timing of the peak GLAI had no significant relationship to the growth rate or to the peak GLAI for either years (Fig. 5).

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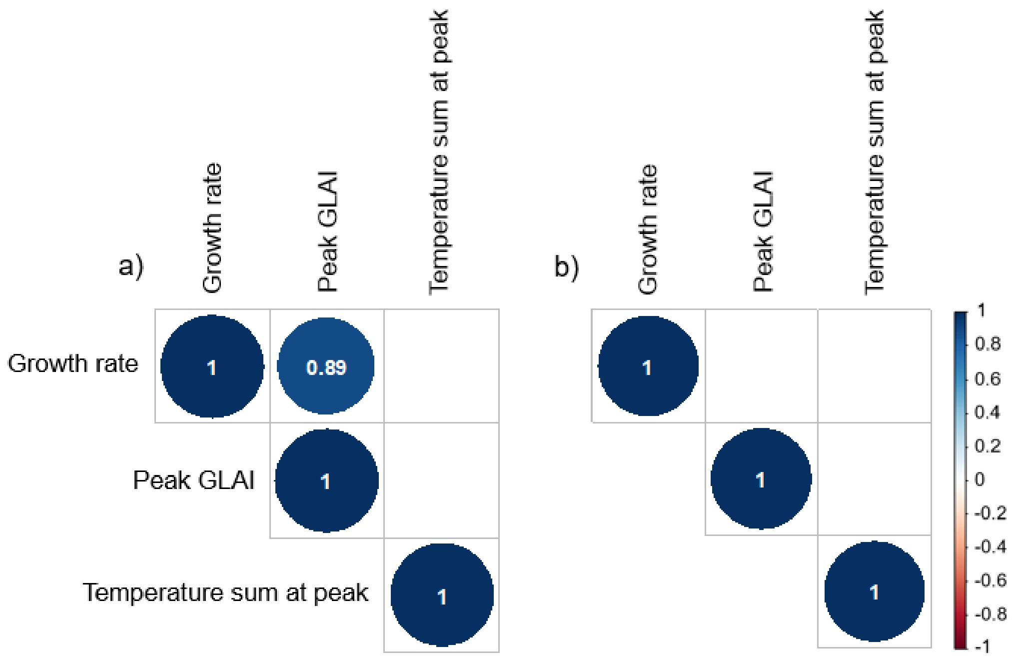

Fig. 5. Spearman correlation coefficients among the crop growth proxies that were derived from green leaf area index (GLAI) dynamics; growth rate, peak GLAI and temperature sum at peak GLAI, during a) dry year (year 2018) and b) year with normal weather conditions (year 2021). Blue colour indicates a positive correlation coefficient (number of fields n = 13).

3.2 Relationships between soil properties and crop development

On average across the thirteen fields, plant available water capacity was 23%, bulk density was 1.5 g cm -3, cation exchange capacity was 16 cmol kg-1, soil organic matter content was 3.6% and clay content was 31% (Tab. S2). Some soil properties were related to each other, with positive correlations between soil organic matter content and cation exchange capacity, and between clay content and cation exchange capacity. Negative relationships were found between clay content and bulk density, and between clay content and plant available water capacity ($p < 0.05$; Fig. S3).

The soil properties explained together 15%, 54% and 27% of the variations across fields in growth rate, peak GLAI and the timing of peak GLAI, respectively, in the year with normal weather conditions (year 2021). However, none of the soil properties was significantly related to growth rate, peak GLAI or the timing of the peak GLAI in 2021 (Fig. 6a). In the dry year (year 2018), the soil properties explained together 44%, 40% and 55% of the variation in growth rate, peak GLAI and the timing of peak GLAI, respectively. Plant available water capacity was significantly related to growth rate in 2018, with a positive association of increased crop growth with higher plant available water capacity ($p < 0.05$). In addition, plant available water capacity explained 21% of the variation in growth rate across fields in the dry year. There were no significant relationships between the other soil properties to growth rate, peak GLAI or the timing of the peak GLAI in 2018 (Fig. 6b).

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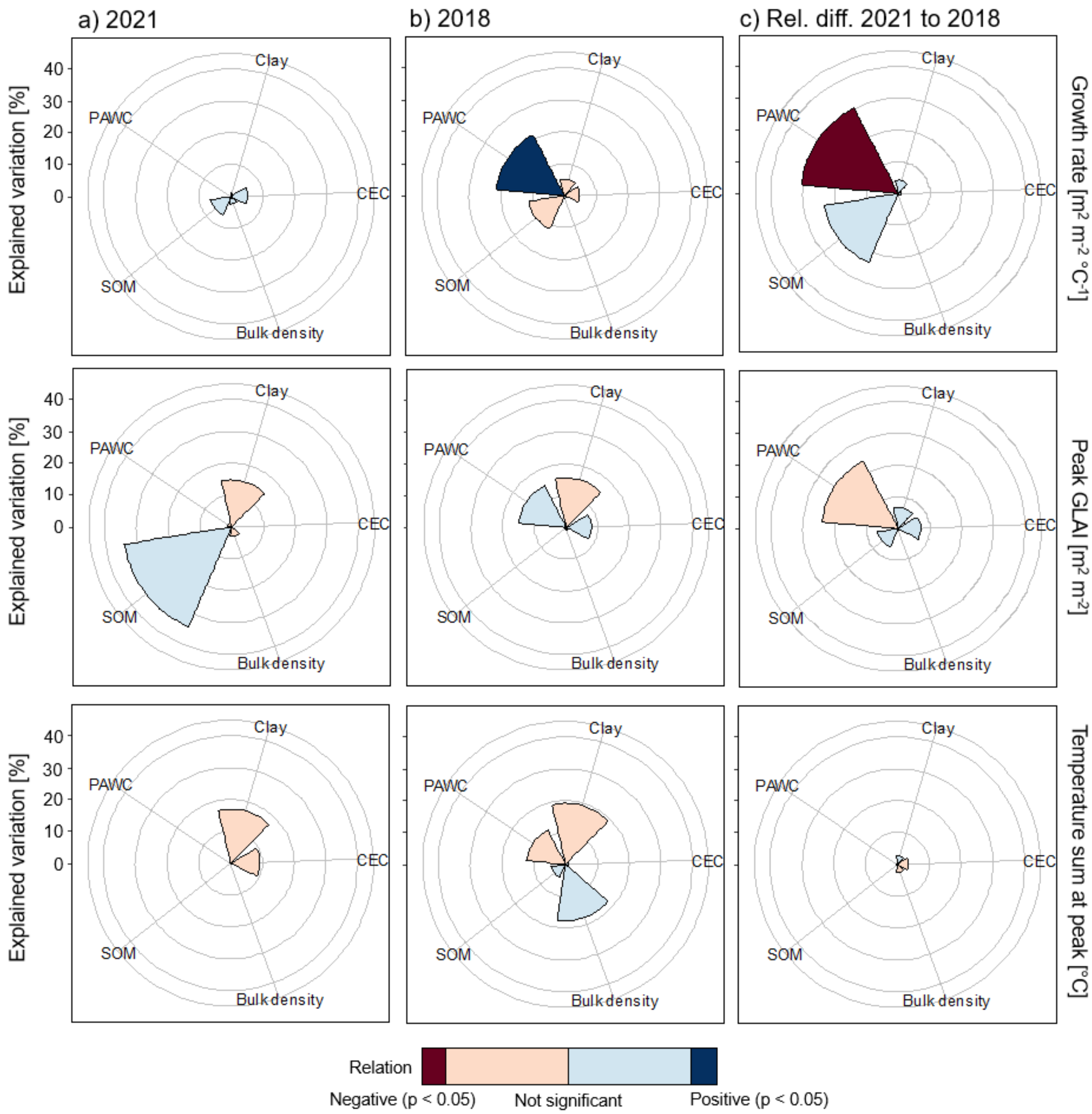
For the relative difference between the year with normal weather conditions (2021) to the dry year (2018), plant available water capacity was the most important soil property. The relative difference in growth rate between the years was negatively related to plant available water capacity ($p < 0.05$), and plant-available water capacity explained 30% of the variation in the difference in growth rates between the years.



245 **Fig. 6. Explained variation, calculated from correlation-adjusted corelation (CAR) scores, by the soil properties clay content, soil organic matter content (SOM), bulk density, cation exchange capacity (CEC) and plant available water capacity (PAWC) on growth rate, peak GLAI and temperature sum at peak GLAI in a) year with normal weather conditions (year 2021), b) dry year (year 2018), and c) the relative difference between the years 2021 and 2018. The p-values and the positive or negative relationships between each soil property and the crop growth proxies were obtained from univariate linear regressions.**

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4 Discussion

4.1 The impact of drought on crop development

In the present study, we used satellite imagery to assess the impact of drought on winter wheat growth and development at the landscape scale. In combination with measurements of soil properties, we could identify specific soil properties that were related to the potential to mitigate the impacts of drought. The early growing season in 2018 was exceptionally dry and warm, resulting in generally reduced winter wheat crop development compared to 2021 that had close to long-term summer average weather conditions (Fig. 4). Previous research has shown negative effects of drought on crop yield at the landscape and country scale (Zipper et al. 2016; Ray et al. 2018; Sjulgård et al. 2023), and lower growth rate and lower peak GLAI during water limited conditions have been found in field trials in which GLAI was measured at the canopy (Meinke et al. 1997; Boedhram et al. 2001). The lower growth and development during drought that we observed in our study demonstrate that Sentinel-2 derived estimates of crop growth proxies can be used to detect drought responses in crop development at the landscape scale.
The dry conditions early in the growing season in 2018 resulted in lower peak GLAI compared to the year with normal weather conditions, with an average difference of 40% between years (Fig. 4). In earlier studies, the peak GLAI has been used to provide yield estimations for different crops (Lambert et al. 2018; Waldner et al. 2019; Yamamoto et al. 2023). Large reductions in winter wheat yields were reported in Sweden during 2018 due to the exceptional drought, with 44% lower total crop production compared to the previous five-year average (SCB 2018). It is interesting that the 44% reduction is similar to average decrease in peak GLAI of 40% observed in our fields. Reduced wheat biomass during drought has been shown in earlier studies (Villegas et al. 2001; Zhang et al. 2018), and according to Villegas et al. (2001), the decrease in biomass und droughtis mainly due to lower growth rate. Similarly, we found lower crop growth rate during the reproductive period in the dry year compared to the year with normal weather conditions, with an average difference between the years of 28% (Fig. 4a). Our results showed no relationships between growth rate and the peak GLAI during the normal weather year, but a positive relationship between growth rate and the peak GLAI in the dry year (Fig. 5). The positive relationship in the dry year shows the importance of a higher growth rate for higher total biomass production during dry conditions, highlighting the importance of faster growth to mitigate drought impacts. The non-significant relationship during the year with normal weather conditions suggest that growth rate is not as critical for biomass accumulation during normal weather conditions.
The peak GLAI was reached earlier (i.e., at a lower temperature sum) during the dry year, and since the peak GLAI has been associated with heading growth stage (Feng et al. 2019), this might indicate a shift in phenology during dry conditions. Some studies have shown that plants might develop faster during drought to reach flowering earlier and complete the life cycle before severe water shortage occurs (Abid et al. 2018; Seleiman et al. 2021). However, we did not find a significant correlation between the timing of the peak GLAI and growth rate or peak GLAI in our data, which would imply that the timing of the heading growth stage did not influence the overall crop performance (Fig. 5). Earlier research studying the impact of the timing of the peak GLAI on wheat yield is not unambiguous: some studies found no relationships between timing of peak GLAI and

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crop yield (Irfan Ullah et al. 2021; Mroz et al. 2023), while an earlier heading have been related to higher wheat yield due to a longer grain filling period in other studies (Tewolde et al. 2006; Mohan et al. 2022).

4.2. The influence of soil properties on crop development

We found differences in crop development between the two years but also between fields. There was a large difference of up to 50-59% increase in growth rate and peak GLAI for certain fields in the crop growth proxies between 2018 and 2021, while there was a smaller difference for other fields (Fig. 3). The timing of peak GLAI increased in some fields and decrease in other fields between the years, however, the differences were small (<9%). Due to similar weather conditions (i.e., similar DMI) across all fields within a specific year, the varying crop responses to drought stress between fields imply that additional factors than the weather must have had an impact on crop development. Here, we show that soil properties had an influence on the crop growth proxies. In 2018, a positive relationship between plant available water capacity and growth rate shows the importance of sufficient soil water retention to sustain crop growth during drought (Fig. 6). In addition, fields with lower plant available water capacity had a larger relative difference in growth rate between the years. Earlier studies have also shown the importance of the soil water status to retain a sufficient amount of moisture during drought (Wang et al. 2009; Huang et al. 2020). Accordingly, the performance of crops grown on soils with high plant available water capacity has been found less affected by changes in rainfall compared to crops grown on soils with low plant available water capacity (Wang et al. 2017). The importance of plant available water capacity for drought resistance found in our study suggests that soil water retention is a crucial soil property that explains crop responses to drought at the landscape level and a key target property to mitigate drought impact by soil management.

The other soil properties assessed in this study were not correlated with estimates of growth rate, peak GLAI or timing of the peak GLAI in 2018, and none of the soil properties was significantly related to the crop growth proxies in 2021 (Fig. 6). Clay content only explained a small part of the variation, but influenced other soil properties such as cation exchange capacity, bulk density and plant available water capacity (Fig. S3). Cation exchange capacity only explained a low part of the variation of the crop growth proxies. All the fields were above the recommended cation exchange capacity for crop production of 10 cmol kg-1 (Tab. S2) (Chowdhury et al. 2021), implying that cation exchange capacity was not a limiting factor for crop development. Our findings that bulk density had no direct relationship with the crop growth proxies may seem to contradict the study of Lipiec et al. (1991) that found decreasing GLAI at the heading stage of spring barley with a higher degree of soil compaction. However, in our fields, bulk density was not critically high, with an average bulk density of 1.5 g cm-3 (Tab. S2). We found no relationships between the estimates of growth rate, peak GLAI or timing of the peak GLAI and soil organic matter content. Earlier studies have shown positive effects of soil organic matter content on soil fertility (Lal 2009; Fageria 2012; Oldfield et al. 2019) and crop productivity during drought (Kane et al. 2021; Mahmood et al. 2023), however, negative effects of soil organic matter content on crop yields have been found in Sweden (Kirchmann et al. 2020).

In our study, soil sampling was conducted in 2021 only. With soil properties changing over time, this may introduce uncertainty in the relationships between the soil properties and the crop development that we established for year 2018. Nevertheless, a

https://doi.org/10.5194/egusphere-2024-1872
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number of studies has shown only small year-to-year changes in soil organic carbon content (Krauss et al. 2020), water content at field capacity (Alam et al. 2014) and bulk density (Alam et al. 2014; Alnaimy et al. 2020) within given soil management systems. In addition to soil properties and weather conditions, crop development is influenced by soil and crop management practices such as fertilization (Agenbag and Maree 1991; Shankar et al. 2021), tillage (Agenbag and Maree 1991; Abagandura et al. 2017), sowing date and crop variety selection (Ihsan et al. 2016; Minoli et al. 2022). We minimised variation in these factors by selecting fields that were managed by the same farmer in 2018 and in 2021. Future research could examine the response of different soil and crop management strategies or the impact of crop variety on drought response to assist farmers in extreme weather mitigation.

5 Conclusion

The impact of drought on winter wheat development was shown by comparing Sentinel-2 derived GLAI development of a dry year and a year with normal weather condition across thirteen fields belonging to commercial farmers in southern Sweden. We observed lower crop growth rate, lower peak GLAI and earlier peak GLAI during the dry year (2018) compared to the year with normal weather conditions (2021). Our data showed the importance of a faster crop growth to obtain more biomass during dry conditions, while the growth rate was less crucial for crop performance during the year with normal weather conditions. The differences in crop development between the years demonstrate that stress related crop response to changing environmental conditions can be detected by monitoring crops using satellite images at the landscape level. The variation in crop growth proxies between fields suggest that differences in soil properties across fields play a critical role for the differences in drought response of winter wheat. We found that plant available water capacity was important for growth rate during the dry year, and that the relative difference in growth rate between the years was lower with higher plant available water capacity. This suggests that water retention is a target soil property to mitigate effects of drought on crop development.

Data availability

The Sentinel-2 scenes were obtained from Microsoft Planetary Computer, and the downloading and processing were performed using the open-source Python Earth Observation Data Analysis Library (EOdal, https://github.com/EOA-team/eodal). The precipitation and temperature data are available from the Swedish Meteorological and Hydrological Institute website https://www.smhi.se/data/ladda-ner-data/griddade-nederbord-och-temperaturdata-pthbv.

https://doi.org/10.5194/egusphere-2024-1872
Preprint. Discussion started: 4 July 2024

Author contributions

Funding was acquired by TC, TK and HA. HS, TK and HA contributed to project conceptualization. HS performed the investigations with advise from LVG, JH, TC, TK and HA. LVG implemented the programming code in EOdal. HS wrote the paper, where the LVG, JH, TC, TK and HA contributed to the review and editing.

Competing interests

The contact author has declared that none of the authors has any competing interests.

Acknowledgements

This work was partly funded by the Swedish Farmers' Foundation for Agricultural Research (Stiftelsen Lantbruksforskning, SLF, grant number: O-19-23-309) and by Formas (The Swedish Research Council for Sustainable Development; grant no: 2022-00218) which is greatly acknowledged. Hanna Sjulgård acknowledges financial support from the Lennart Hjelm's foundation, Lukas Valentin Graf acknowledges funding by the Swiss National Science Foundation for the project "PhenomEn" (grant number IZCOZ0_198091) and Tino Colombi acknowledges funding from the University of Nottingham (Nottingham Research Fellowship). The authors want to thank all the farmers involved in this study for allowing soil sampling on their fields. We also thank Laura Martínez, Leah Eitelberg and Loraine ten Damme for help with the soil sampling, and Ana María Mingot Soriano, Anna Oskar and Jan Fiedler for laboratory measurements.

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