Vegetation phenology from Sentinel-2 and field cameras for a Dutch barrier island

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ABSTRACT

Remote sensing studies of vegetation phenology increasingly benefit from freely available satellite imagery acquired with high temporal frequency at fine spatial resolution. Particularly for heterogeneous landscapes this is good news, given the drawback of medium-resolution sensors commonly used for phenology retrieval (e.g., MODIS) to properly represent the fine-scale spatial variability of vegetation types. The Sentinel-2 mission acquires spectral data globally at 10 to 60 m resolution every five days. To illustrate the mission's potential for studying vegetation phenology, we retrieved phenological parameters for the Dutch barrier island Schiermonnikoog for a full season of Sentinel-2A observations in 2016. Overlapping orbits resulted in two acquisitions per 10 days, similar to what is achieved globally since the launch of Sentinel-2B. For eight locations on the island's salt marsh we compared greenness chromatic coordinate (GCC) series derived from digital repeat RGB-cameras with vegetation index series derived from Sentinel-2 (NDVI and GCC). For each series, a double hyperbolic tangent model was fitted and thresholds were applied to the modelled data to estimate start-, peak-, and end-of-season (SOS/PS/EOS). Variability in Sentinel-2 derived SOS, when taken as the midpoint between minimum and peak NDVI, was well-explained by camera GCC-based SOS (R\textsuperscript{2} = 0.74, MSD = 8.0 days, RMSD = 13.0 days). However, EOS estimates from camera GCC series were on average almost two months before NDVI-based estimates. This could partially be explained by the observed exponential relationship between GCC and NDVI, as well as by the combined effect of viewing angle differences and the presence of non-photosynthetic elements in the vegetation canopy. A two-layer canopy radiative transfer model incorporating reduced chlorophyll levels in the upper layer provided a physically-based explanation of the viewing angle effect. Finally, we applied the phenology retrieval approach to NDVI series for all pixels of the island in order to map spatial patterns of phenology at fine resolution. Our results demonstrate the potential of the Sentinel-2 mission for providing spatially-detailed retrievals of phenology.

1. Introduction

The timing of periodic events in plants, like budburst or flowering, is generally referred to as plant phenology. Food availability for animals is affected by this timing, and as such plant phenology impacts on animal migration and breeding patterns (Duraart et al., 2007; Miles et al., 2017; Shariati Najafabadi et al., 2015). Plant periodic events have a strong relationship with seasonal changes in moisture availability, temperature, and radiation (Stöckli et al., 2008), but are also affected by extreme weather events (Jentsch et al., 2009). To better understand how climate change may impact on plant and animal populations, accurate monitoring of plant phenology in space and time is important (Cleland et al., 2007).

The traditional approach of monitoring plant phenology uses frequent visual observations to detect the timing of specific events like flowering, for example by trained personnel in phenological gardens (Schnelle and Volkert, 1964) or by volunteers (Newman et al., 2012; Schwartz et al., 2012; van Vliet et al., 2014). An alternative approach,
requiring less frequent field presence, is the use of fixed-position digital cameras that take several photographs of the vegetation each day. This so-called digital repeat photography has been implemented in various networks in Australia (Moore et al., 2016), Europe (Wingate et al., 2015), Japan (Nasahara and Nagai, 2015), and North America (Klosterman et al., 2014). Besides identifying discrete events, analysis of temporal changes in the relative brightness of red, green, and blue (RGB) channels allows for a more continuous tracking of canopy greenness (Richardson et al., 2009). Studies showed that this can be achieved effectively with relatively cheap consumer-grade RGB cameras (Nijland et al., 2014; Sonnentag et al., 2012), even if an additional near-infrared spectral band may provide complementary information similar to satellite-derived vegetation indices (Petach et al., 2014). In the past ten years, greenness series from digital repeat photography have been used extensively for assessing phenology and its relationship with primary productivity and climate, predominantly in forests (e.g., Klosterman et al., 2014; Menzel et al., 2015), but also in other ecosystems like alpine grasslands (Migliavacca et al., 2011), tropical savannas (Alberton et al., 2014), or Arctic vegetation (Anderson et al., 2016).

Even if tower-mounted or mountain slope-viewing cameras may observe larger areas, landscape-scale observation of phenology can only be achieved from satellites. Because this equally requires frequent observation, satellite-based phenology studies mostly relied on medium- to coarse-resolution (250 m to 8 km) optical imagery from sensors like the Moderate Resolution Imaging Spectroradiometer (MODIS) that is acquired at daily intervals (Reed et al., 1994; Vrieling et al., 2011; Zhang et al., 2003). The high frequency is needed to ascertain a sufficient number of cloud-free observations throughout the growing season. Since at the medium spatial resolution individual plants cannot be discerned, we generally refer to “land surface phenology” to describe the aggregate temporal behaviour of the multiple plant species and vegetation communities present within a grid cell (de Beurs and Henebry, 2005). Although regional and global patterns of land surface phenology can be effectively captured by these medium-resolution sensors, such sensors may not properly represent the actual phenological variability, particularly in areas with heterogeneous land cover (Melaas et al., 2013; Vrieling et al., 2017).

Finer-resolution (< 30 m) satellite acquisitions usually come at the expense of longer revisit times, generally resulting in too few cloud-free observations to effectively describe seasonal changes in greenness. One option to obtain finer-resolution estimates of land surface phenology is to fuse sparse fine- with frequent medium-resolution acquisitions (generally Landsat and MODIS, e.g., Frantz et al., 2016; Walker et al., 2014; Zhang et al., 2017). Although image fusion has received much attention in recent years, it remains sub-optimal for representing rapid changes, particularly in heterogeneous landscapes (Emelyanova et al., 2013; Gao et al., 2015; Zhu et al., 2010). An alternative is to combine vegetation indices from fine-resolution data, typically Landsat, from multiple years into a single synthetic year (Fisher et al., 2006). From this, multi-annual average estimates of phenological transition dates can be made that can be adjusted annually based on sparser individual-year observations (Melaas et al., 2013; Melaas et al., 2016). This approach has proven to be successful for deciduous forests at locations where two Landsat tiles overlap, but cloud cover around transition dates limited the possibility for annual adjustment of the estimates, particularly for other land covers that have little seasonal variability in greenness and/or strong year-to-year variations its temporal behaviour (Nijland et al., 2016; Vrieling et al., 2017).

Taking advantage of new fine-resolution optical sensors with reduced revisit times, recent studies retrieved phenology directly from fine-resolution imagery without image fusion or combining data from different years. For example, Pan et al. (2015) assessed crop phenology of winter wheat and maize in central China using three years of 30-m resolution data from the two optical HJ-I (Huan Jing) satellites. For forest sites in Vermont (United States), White et al. (2014) estimated start of season from combined Landsat TM and ETM+ imagery of two overlapping orbits and compared results with field estimates of bud burst. For the same site as the present study (Schiermonnikoog, The Netherlands), Vrieling et al. (2017) combined RapidEye and SPOT5 imagery of 2015 to retrieve spring phenology estimates. In that study, comparison with coarser resolution series (e.g., MODIS) demonstrated the additional information content of the fine-resolution retrievals, but ground data to assess the accuracy of the retrievals was not available.

This study builds on those efforts and offers a first attempt to retrieve vegetation phenology from the Multi Spectral Instrument (MSI) of the Sentinel-2 mission. This is the first mission that provides free publicly-accessible data at 10-60 m resolution (10 m in four spectral bands) every five days with global coverage (Drusch et al., 2012). Although the five-day repeat frequency is only achieved since the launch of Sentinel-2B in March 2017, for Schiermonnikoog we already obtained two acquisitions per 10 days in 2016 with Sentinel-2A using two overlapping orbits, thereby more closely simulating the Sentinel-2A and -2B configuration. The goals of this study are (1) to compare retrievals of phenology from digital repeat photography and Sentinel-2A time series for the dynamic salt marshes of Schiermonnikoog (the Netherlands); (2) to explain differences between both retrievals; and (3) to map phenology at 10 m resolution from Sentinel-2A time series.

2. Study area and data

2.1. Study area

Schiermonnikoog is a barrier island located in the north of the Netherlands between the North Sea and the intertidal Wadden Sea (Fig. 1). About 85% of the 40 km²-large island is a National Park, with the remainder containing grasslands, maize, and built-up area. The National Park contains dunes, marshes, and beaches, which together host a rich fauna and flora. The island’s salt marshes are regularly flooded during high tides. Small altitudinal differences affect the frequency and duration of flooding and as such the vegetation composition (Offl et al., 1988). Tides, wind, and grazing together make the natural vegetation dynamic and spatially variable. Herbs and grasses of different species and height are found across the island, while the dune area in addition contains forest and shrub vegetation.

2.2. Field camera time series

We installed eight Bushnell Trophy Cam Essential (model 119736) trail cameras across the salt marsh of Schiermonnikoog (Fig. 1) that collected 3-megapixel RGB photographs in JPEG format. White balance and exposure are determined automatically by these cameras, and cannot be adapted by the user. Despite that these cameras do not provide calibrated radiance measurements, Sonnentag et al. (2012) showed that phenology-relevant information is retained irrespective of camera choice and JPEG compression. We programmed the cameras to collect ten photos per day, i.e. every half hour between 10:30 and 15:00 CET. Six of the eight cameras (A-F) were placed along a transect from the low marshes to the higher dune area, purposively selecting relatively homogenous areas. Camera G was mounted to view a patch of reed vegetation that was not present near the transect. Cameras A–G were installed on 3 March 2016, while camera H was installed already in 2015 at a grassland site with better accessibility. Cameras A–G can only be reached by foot, and the salt marsh area is closed for public during the bird breeding season from 15 April to 15 July, hence limiting interference by humans. Fig. 2 provides sample photos for each camera.

All cameras faced north to avoid direct incoming sunlight and were mounted on poles at an approximate height of 2.2 m above the ground surface with a depression angle of ~8°, resulting in a detailed view of the area between 10 and 30 m north of the camera location. Metal pins were fixed on top of the poles to avoid disturbance by birds. We noted...
that the camera field-of-view showed small deviations over time, but because the areas of interest were near the camera this had little effect on the observed area. Image series were collected by replacing memory flash cards on 26 July 2016 and 7 March 2017, although camera H was serviced more frequently. Four cameras did not function as expected for the full time period due to moisture entering the camera (B, E, F) or technical failure after card replacement (G), but nonetheless provided useful data for part of the season. We manually removed any photos that were blurred (due to humidity on the lens), over- or underexposed, or that contained surface water in the scene due to tidal inundation.

For all but one image frames we identified a single area of interest. For camera H two distinct areas were identified including a non-grazed fenced-off foreground area and a background area grazed by cattle. Per photograph and for all pixels within the area of interest we calculated the greenness chromatic coordinate \( \text{GCC}_{90C} \) as follows:

\[
\text{GCC}_{90C} = \frac{G}{R + G + B}
\]  

where \( R, G, \) and \( B \) are the digital numbers corresponding to the red, green and blue channels respectively, contained in the JPEG image (Gillespie et al., 1987), and the subscript \( c \) refers to the fact that here \( \text{GCC}_{90C} \) was calculated from camera data. Although other indices exist, \( \text{GCC}_{c} \) is commonly applied to camera time series for phenology studies (Migliavacca et al., 2011) and can well suppress effects of variable scene illumination (Sonnenberg et al., 2012). We averaged the \( \text{GCC}_{c} \) values for each area of interest, and to reduce noise we calculated the 90th percentile of all averaged \( \text{GCC}_{c} \) values within non-overlapping three-day windows \( \text{GCC}_{90C} \) following Sonnenberg et al. (2012).
2.3. Sentinel-2 imagery

We downloaded all 33 available (partially) cloud-free acquisitions of Sentinel-2A over Schiermonnikoog between February 2016 and February 2017, i.e. starting and ending in winter with minimal green cover. This resulted on average in 27.6 (± 1.7) valid observations per pixel for the island. The acquisitions were made from two different orbits separated by three days, having similar viewing zenith angles (5.2 vs 7.8°) and opposite viewing azimuth angles (104.4 vs 288.6°). We atmospherically corrected the imagery using the Sen2Cor processor (version 2.3.0) to obtain Level-2A surface reflectance products (Louis et al., 2016). For each image we used Sen2Cor’s Scene Classification output to discard any pixels classified as saturated or defective, cloud shadow, medium to high cloud probability, thin cirrus, or snow/ice. From the 10 m resolution spectral bands 2, 3, 4, and 8, we then calculated NDVIs and GCCs (subscript s for satellite), which were selected here because they represent commonly-used vegetation indices for respectively satellite- and camera-based phenology studies. It is noted that while satellite indices are computed with surface reflectance, camera indices are computed with raw digital numbers that scale with reflected radiances.

3. Methods

3.1. Phenology retrieval from index time series

A double hyperbolic tangent function was fitted to all vegetation index (VI) time series, i.e., NDVIs, GCCs, and GCC90c. The function is equivalent to the double logistic model (Beck et al., 2006) and can be written as (Meroni et al., 2014):

\[ V_I(t) = a_0 + a_1 \tanh[(t - a_2)s_a] + 1 + a_4 \tanh[(t - a_6)s_a] + 1 - a_4 \]

where \( t \) is time (days). We fitted the function with the Levenberg-Marquardt least squares method as implemented in the IDL-routine MPFIT (Markwardt, 2008), whereby we constrained parameters to remain within a reasonable range. This routine requires an initial estimate of the parameter values. The following list describes the parameters and indicates in italics how the initial parameter estimates were obtained:

- \( a_0 \): the minimum VI value. The minimum VI in the first half of the time series;
- \( a_1 \) [\( a_4 \)]: the VI amplitude of the green-up [senescence] phase. The difference between the maximum VI and the minimum VI in the first [second] half of the time series;
- \( a_2 \) [\( a_6 \)]: the inflection point (days) for the green-up [senescence phase]. The midpoint between the start [end] of the time series and the time of maximum VI;
- \( a_3 \), \( a_5 \): control the slope at the inflection point for both phases (day⁻¹). Initialized at 0.02 [−0.02].

Because VIs tend to be biased towards lower values due to remaining atmospheric effects, undetected clouds, and inundation, an iterative procedure was applied to fit the function to the upper envelope of the data following a similar weighting procedure as described in Chen et al. (2004). We fitted the function only for the support temporal range of 11 February 2016 to 15 February 2017. This corresponded to respectively the first and last Sentinel-2A image used in the satellite series, which was taken as a full year ranging between two minimum (winter) VI values (see also Fig. 3). Based on the fitted model and the temporal range, four phenological parameters were determined using a threshold approach (White et al., 1997) as follows:

- \( \text{SOS}_{20} \): start of season, defined as the first moment when the fitted function reaches 20% of the amplitude between maximum VI and the fitted value for 11 February 2016;
- \( \text{SOS}_{50} \): start of season, similar as \( \text{SOS}_{20} \) but using a 50% threshold;
- \( \text{PS}_{50} \): peak season, the first moment when the function reaches 90% of the amplitude;
- \( \text{EOS}_{20} \): end of season, defined as the first moment of the senescence phase when the fitted function reaches 50% of the amplitude between maximum VI and the fitted value for 15 February 2017.

Two SOS measures (\( \text{SOS}_{20} \) and \( \text{SOS}_{50} \)) were tested following the various SOS thresholds used in literature, with \( \text{SOS}_{50} \) representing an early green-up signal and \( \text{SOS}_{20} \) corresponding to the fastest increase in green-up (White et al., 2014). Rather than using the moment of maximum VI of the season, we selected \( \text{PS}_{50} \) as a more stable measure given that the fitted function for satellite VI series frequently resulted in a stable plateau of relatively large VI values during summer that persisted between one and five months.

This retrieval procedure was applied to NDVI, and GCCs series of each Sentinel-2 pixel within the island boundaries (Fig. 1), including those Sentinel-2 pixels corresponding to the areas of interest observed by the field cameras, as well as to the field camera GCC90c, series. For two cameras (B and G) no data were acquired after August 2016. Because only the green-up phase could be modelled for those cases, we applied a single hyperbolic tangent model as in Vrieling et al. (2017) taking as the support temporal window 11 February to 1 August 2016. In this way we could still use the data from those cameras to estimate \( \text{SOS}_{20} \), \( \text{SOS}_{50} \), and \( \text{PS}_{50} \).

3.2. Radiative transfer modelling

We hypothesized that satellite and camera (GCCc and GCC90c) time series may have different temporal trajectories due to:

1) the difference in view zenith angle only (VZA, being near-nadir for the satellite and about 70° for the camera);
2) the different VZA in combination with the observed presence of dry material during the green-up phase (i.e. the dead phytomass of the previous year) and of non-photosynthetic organs (i.e. flowers and dry reproductive organs) after maximum leaf development;
3) the difference in spectral sensitivity between the Sentinel-2A MSI and the Bushnell cameras.

With regard to the third hypothesis, the actual response of the Bushnell cameras could not be reproduced because the exposure and white balancing for this type of cameras are fixed to automatic. In addition the camera spectral response function for the RGB channels was not available. Therefore, we restricted the analysis to evaluate what Sentinel-2A’s MSI would observe from the camera viewpoint. We did not specifically address possible differences in sun elevation angles, because a) the satellite acquisition time (i.e., between 11:40 and 11:56 CET) was within the daily observation window of the field camera, b) we found no evidence of daily GCCc trends, but rather found that cloud-induced illumination differences had the strongest effect on daily GCCc variation, and c) the GCC90c measure results from various observations and is not related to a single timing.

To test the first two hypotheses we used the two-layer canopy bidirectional radiative transfer (RT) model 4SAIL2 (Verhoef and Bach, 2003) coupled with the leaf optical properties model PROSPECT5B (Féret et al., 2008; Jacquemoud and Baret, 1990) that simulates the reflectance and the transmission of a leaf as a function of its constituents. The 4SAIL2 model follows a four-stream concept and it is the two-layer version of the model SAILH (Verhoef, 1984), a one-dimensional bidirectional turbid medium radiative transfer model that also describes the hot spot effect in plant canopy reflectance (Kuusk, 1991). We simulated the temporal evolution of GCC90c for the nine locations corresponding to areas of interest defined on the camera frames using...
different assumptions on RT set-up and model parameters in an attempt to provide a possible physical explanation for the mismatch.

For each camera location we ran three simulation sets with different parameterization intended to represent the two working hypotheses: 1) a canopy described by a single layer with homogeneous leaf and canopy properties (RT-1layer); 2) an addition of a second top layer with reduced chlorophyll content that reflects the dominance of dry vegetation carried over from the previous year and the appearance of flowers and grass stems later in the season (RT-2layer); and 3) a further reduction of the chlorophyll content of the upper layer to represent the continuing presence of non-photosynthetic elements during the season (RT-2layer*). Simulations 2 and 3 differ by the value of the maximum chlorophyll content of the upper layer. With RT-1layer we tested if the different view angle alone could explain the observed differences when considering the development of a simple and homogeneous green canopy. With RT-2layer and RT-2layer* we still tested the viewing angle effect, but attempted to provide a more realistic description of the canopy development as depicted by the camera image time series. Camera pictures show that relatively tall and dry phytomass material dominant at season start is progressively less visible as vegetation grows. Close to the timing of maximum biomass expansion, flowering, stem elongation, and seed formation take place above the canopy plane. This inflorescence progressively dries out during autumn. To represent such dynamics in our simplified RT modelling scheme, we modelled a lower layer with spherical leaf angle distribution and an upper layer occupying 20% of the total height with erectophile leaf angle distribution. While chlorophyll content was kept constant for the lower layer, we initiated the chlorophyll content of the upper layer at 0 for February 2016 and increased it in proportion to LAI to reach the same level as the lower layer at the time of maximum LAI to mimic the gradual replacement of dead phytomass with new green vegetation. After maximum LAI we reduced the upper level chlorophyll using an exponential decay function with a half-life of 30 days to represent the rapid increase of non-photosynthetic material related to flowering and seed/stem formation. For RT-2layer* we further reduced the maximum chlorophyll level of the top layer by 25%. We acknowledge that this modelling setup can only be a rough representation of the real vegetation dynamics, which in reality also vary between camera locations. However, our main purpose was not to construct a model that accurately mimics the temporal dynamics of the observed GCC time series, but rather to assess if the observed differences in retrieved phenological parameters (i.e., due to viewing angle differences between satellite and field camera) can be reproduced with a physically-based explanation.

Canopy reflectance is computed for each available Sentinel-2A overpass using the illumination geometry (i.e. sun zenith and azimuth angles) at time of overpass. Satellite VZA is fixed to 0° (i.e. nadir-view) and the camera VZA to 70° (i.e., the average view angle of the camera ROI). The camera view azimuth angle was set to 0° as all cameras face North. In all simulations, the background reflectance is considered Lambertian and set to the average of three measurements acquired in situ with an ASD-Fieldspec 3 and a nadir view. To represent a plausible temporal vegetation development at the various sites we used the LAI retrieved from radiative transfer model inversion on Sentinel-2A data over the period of interest (O’Connor et al., 2017). Other model parameters were set to the camera site mean retrieved value. A summary of the used parametrization is reported in Table 1.

Fig. 3. Time series of NDVI and GCC derived from Sentinel-2A, and GCCc and GCC90c, derived from the field cameras. Each panel relates to the corresponding camera identifier. For camera H two areas of interest are defined, corresponding to panels h1 and h2 in this figure. The fitted double hyperbolic tangent functions are plotted for each series (single for camera series E and G), and the corresponding retrievals for SOS20, SOS50, P50, and EOS50 are indicated as vertical lines at the bottom of each panel.
Following the simulations, the spectral simulation outputs (at 1 nm interval) were resampled to Sentinel-2A's bands 2 (blue), 3 (green), and 4 (red) using the spectral response functions of the instrument (European Space Agency, 2017). Based on the simulated reflectances for these bands, we then calculated GCC for both VZA's. Finally, we applied the same procedure as in Section 3.1 to retrieve phenological parameters from the simulated GCC90c time series.

### 3.3. Statistical analyses

To assess if the fitted function (Eq. 2) closely matched observations, we assessed the model fit using the Pearson correlation coefficient (r) between the observed and fitted vegetation index values for each time series, as well as the corresponding root mean square deviation (RMSD) and mean signed deviation (MSD).

To compare phenological retrievals from field camera and Sentinel-2 series, we calculated the R², RMSD, and MSD for each phenological parameter. The same was done for the comparison of the phenology estimates from simulated GCC data at different viewing angles. To evaluate if the difference between camera- and satellite-derived phenological retrievals can be reproduced by RT-model simulations, we focused on the MSD between the phenological timing derived from the two viewing geometries. In other words, we were interested in testing if the observed shift between camera- and satellite-derived timings could be explained by the different modelling set-ups. For this, differences in MSD were tested by ANOVA Randomized Block Design and Tukey's honest significant difference (HSD) test using the conventional 0.05 significance level.

To assess to what extent the selected VI may impact the phenology retrievals, we empirically modelled the relationship between Sentinel-2 derived GCC, and NDVI, for this, an exponential function was selected after visual inspection of the scatterplot of the two variables. We also calculated the root mean square error (RMSE) and mean signed error (MSE) for this relationship; because the dependent variables are observed rather than estimated values, we replace ‘deviation’ with ‘error’ here.

Finally, we assessed how reduced Sentinel-2 image availability may impact the retrieval of phenological parameters. We first split the data into acquisitions by relative orbit 8 and 51 to examine whether acquisitions from a single orbit would have resulted in similar retrievals. Subsequently, we simulated reduced image availability due to periodic persistency of cloud cover by iteratively excluding all observations from a single month. We focussed this analysis on Sentinel-2 derived NDVI only and limited it to the pixels corresponding to the nine areas-of-interest observed by the field cameras, as defined in Figs. 1 and 2. We calculated the MSD and RMSD to summarize deviations between retrievals from the reduced data set versus the full data set.

### 4. Results

#### 4.1. Phenological retrievals: Camera versus satellite

Temporal profiles of camera-derived GCC, and GCC90c, and satellite-derived NDVI, and GCCc are displayed in Fig. 3, together with the fitted functions and the four extracted phenology parameters for each series. GCCc is plotted on the secondary y-axis as it is smaller than GCCc. The cause of this difference can be that GCCc is computed from reflectance values while GCCc is derived from raw digital number proportional to reflected radiance. In addition, cameras do apply an automatic scaling (i.e. the white balance) to the RGB channels.

Fig. 3 illustrates that Sentinel-2 observations are reasonably spread throughout the year. Only three observation gaps of more than a month existed; 40 days between 7 June and 17 July, 40 days between 25 October and 4 December (for camera H, slightly shorter for others), and 43 days between 4 December and 16 January. The temporal behaviour could be accurately modelled with Eq. (2) resulting in an average Pearson correlation coefficient (r) of 0.88 for NDVIs and 0.89 for GCCc, between fitted and original values. For the GCC90c, series, r was 0.95. For Figure 3h1 all indices show a decrease in greenness in July/August followed by a subsequent increase; this is caused by intrusion of cattle in the normally fenced-off area resulting in a trampling and reduction of green grass cover followed by regrowth. Despite this “intervention” we fitted the same model to the series.

Fig. 3 shows that the green-up phase is more similarly timed between camera and satellite series, as compared to the reduction of greenness during or after summer. The GCC90c series generally display an earlier and faster decrease in greenness as compared to the satellite series. This may be partially attributed to the development of non-photosynthetic elements like flowers, grass stems, and seed heads, which are dominant in the oblique view of the field camera but less important in nadir view because of their predominantly vertical elongation and higher position in the canopy. Fig. 4 illustrates this with selected photographs for cameras B, C, and D. The numbers in Fig. 4 show that NDVI remains above 80% (of the green-up amplitude) throughout September for the selected camera locations, while GCC90c reduces much quicker. For camera B this is mostly due to the presence of common sea-lavender (Limonium vulgare), for which the purple flowering peaks in August but its flowers remain dominant on the photograph also after fading. For camera C, sea couch (Elytrigia atherica) grass forms stems with vertically-oriented seed heads that elongate and gradually lose their green colour from August onwards. Camera D contains a mixture of the effects of grass stems and heads (Festuca rubra), and flowering (Juncus gerardii and Limonium vulgare).

Phenological parameters retrieved from GCC90c, series are plotted against their equivalents retrieved from the NDVI, and GCCc time series in Fig. 5. On average, satellite retrievals are earlier than camera retrievals for SOS20 (MSD = 19 days for NDVI, and 1.7 days for GCCc), and gradually become later than the camera retrievals going from SOS50 via P50 to EOS50. For NDVI-retrievals the RMSD is lowest (13.0 days) for SOS50, for which the satellite retrievals explain 74% of the variability of camera retrievals. For GCCc, SOS50 is the retrieved parameter that corresponds closest to camera retrievals (R² = 0.72, RMSD = 6.7 days). NDVI-based retrievals are generally earlier than GCCc-based retrieved by 9 to 18 days, except for EOS50 for which the GCCc-based retrieval is about a month earlier on average (MSD = −26.6 days for GCCc, −55.0 days for NDVI). The largest RMSD is also found for EOS50 (61.6 days for NDVI, 35.0 days for GCCc), in line with our earlier observations (Figs. 3 and 4).
We found that GCC has an exponential relationship with NDVI (Fig. 6) that does not vary over time. GCC is more sensitive to differences in NDVI, for large NDVI values (i.e., larger green biomass) as compared to smaller values. To evaluate if the exponential relationship can explain part of the differences between NDVI- and GCC-derived phenological parameters, we transformed NDVI into GCC* using the Equation in Fig. 6a. Table 2 indicates that the transformation indeed makes phenological retrievals more similar to those derived from GCC. For each phenological parameter the R^2 increases, while MSD and RMSD decrease. This demonstrates that a non-linear relationship between VIs is translated into a different shape of the VI temporal evolution and hence of the retrieved phenological parameters.

4.2. Viewing angle effects from radiative transfer modelling

Fig. 7 illustrates for two camera locations (camera C and D) the simulated GCC and GCC* models. Assuming that the LAI retrievals are accurate, the RT-1layer model resulted in a poor description of the GCC temporal pattern (Fig. 7a, d), compared to the observed
The addition of a top layer with varying chlorophyll levels over the season (Fig. 7b, c, e, f) produced more realistic patterns. As expected, these still do not match perfectly with observations because of our rough assumptions about depth of the top layer and chlorophyll dynamics that are uniformly applied to all locations and because of inherent difficulties in modelling an actual canopy with a turbid medium approach. Nonetheless, the model results illustrate that the addition of this less-photosynthetic top layer offers a physically sound explanation for the earlier EOS50 observed for GCCc as compared to GCCs. For the green-up phase, retrievals from observed SOS20, SOS50, and PS90 are earlier for GCCc than those for GCCs for camera locations C and D (Fig. 3c, d). While the sign of this difference is reflected in the retrieved SOS20, SOS50, and PS90 from the two-layer

Table 2
Comparison of phenological retrievals from GCCc series with NDVI, and GCCc* series for the camera locations. GCCc* refers to the transformed NDVI, series applying the empirical relationship of Fig. 6a.

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<td>NDVI</td>
<td>GCCc</td>
<td>NDVI</td>
</tr>
<tr>
<td>R²</td>
<td>0.54</td>
<td>0.69</td>
<td>0.83</td>
<td>0.87</td>
</tr>
<tr>
<td>MSD</td>
<td>17.33</td>
<td>5.44</td>
<td>15.11</td>
<td>5.22</td>
</tr>
</tbody>
</table>

Fig. 6. Relationship between NDVI and GCC derived from Sentinel-2 time series for (a) pixels corresponding to camera locations, and (b) all pixels on the island.

Fig. 7. Temporal profiles of GCC from a nadir satellite perspective and the oblique camera perspective derived from the radiative transfer modelling for the locations of camera C (a, b, c) and D (d, e, f). Panels a and d show results for RT-1layer, panels b and e for RT-2layer, and panels c and f for RT-2layer*. For GCC, the lines show the fitted double hyperbolic tangent model. In addition, the simulation input values for LAI and Chl are shown. For RT-2layer simulation panels, the Chl profile refers to the Chl in the upper layer, Chl in the lower layer being kept constant as in panels a and d.
models, the magnitude of the differences vary. The further reduction of chlorophyll levels in the RT-2layer* model resulted only in small changes for the retrieved phenological parameters.

Combining all camera locations, Table 3 summarizes the differences between GCCc- and GCCc-based phenological retrievals for observed and simulated data. It confirms that the RT-1layer model could not reproduce the differences of the observed data; MSD between camera- and satellite-view retrievals deviate by at least 20 days compared to observations. For the two-layer models, the match between MSD values is much better, particularly for the 50%-threshold parameters (SOS50 and EOS50). For example, for these parameters the MSD and RMSD for observed and RT-2layer* match within a day. For all phenological parameters, the MSD of RT-1layer is significantly different from the MSD of observed data, RT-2layer and RT-2layer*, based on Tukey’s HSD test. On the contrary, and again for all phenological parameters, the MSD of RT-2layer* is not significantly different from the MSD of observed data. The same is true for the MSD of RT-2layer with the exception of SOS20. This indicates that even though we used a single and simple representation of the top layer’s evolution, it can explain a large part of the variability between phenological retrievals derived from nadir versus oblique viewing angles.

4.3. Mapping of phenological parameters

Fig. 8 shows the result of applying the phenological retrieval approach to all individual Sentinel-2 pixels within the island boundaries. For 77.5% of the pixels the retrieval was successful, i.e. it could be initiated and converged. Particularly for classes with limited NDVI variability throughout the year (Kpp and Sv) retrieval of phenological parameters often failed, and also the Pearson correlation coefficient for successful retrievals is smallest of all classes (Table 4). On average for the island, SOS20 is reached on 20 April, SOS50 on 12 May, PS90 on 13 June, and EOS50 on 16 November. However, there is a large spatial variability both within and between vegetation communities (Table 4). Average dates for SOS20, SOS50, and PS90 increase going from the middle-high marshes (Km) to the pre-pioneer zone marshes (Kpp). Maize behaves distinct from the other classes; it has the smallest standard deviation for SOS50 and PS90 of all classes, a late green-up and the earliest EOS50 due to the ripening and harvest early October. As a consequence, all maize fields are clearly visible in Fig. 8.

The difference between phenology retrievals from NDVI and GCCc series is shown in Fig. 9. The maps confirm our earlier findings (e.g., Table 2) that SOS20, SOS50, and PS90 are generally earlier for NDVIs-based retrievals (on average by 7.0, 7.3, and 6.7 days respectively), while EOS50 is earlier for retrievals from GCCc (5.4 days). Substantial spatial variability exists between these differences. NDVI amplitude could explain a small fraction of this variability with significant Pearson correlation coefficients between green-up amplitude and SOS20, SOS50, and PS90 of −0.230, −0.296, and −0.236 respectively.

4.4. Effects of reduced image availability

Table 5 summarizes how reduced image availability would have affected the retrievals from Sentinel-2 derived NDVI for the nine camera locations. The largest effects are found when only acquisitions from a single relative orbit are used, because this reduces data availability to about half of the full data set. The relative large RMSD values suggest that single-orbit acquisitions for Schiermonnikoog miss out important elements of the changes in greenness, and are therefore insufficient to accurately retrieve phenology. Excluding all acquisitions of a single month to mimic persistent cloud cover had varying effects, depending on which month was excluded. RMSD values were largest when February imagery (both at start and end of the period) was omitted, and second largest for SOS20 and SOS50 when removing August imagery. This underlines the importance for phenology studies of image availability not only during vegetation growth, but also during winter (minimum NDVI) and peak season. Instead for EOS50, removing a single

---

Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SOS20</th>
<th>SOS50</th>
<th>PS90</th>
<th>EOS50</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSD</td>
<td>1.7</td>
<td>19.7</td>
<td>−9.4</td>
<td>−8.2</td>
</tr>
<tr>
<td>RMSD</td>
<td>6.7</td>
<td>23.6</td>
<td>10.9</td>
<td>9.8</td>
</tr>
<tr>
<td>MSD</td>
<td>−7.1</td>
<td>−28.3</td>
<td>−10.0</td>
<td>−7.3</td>
</tr>
<tr>
<td>RMSD</td>
<td>10.5</td>
<td>32.7</td>
<td>11.7</td>
<td>9.5</td>
</tr>
</tbody>
</table>

Fig. 8. Retrievals of SOS20 (a), SOS50 (b), PS90 (c), and EOS50 (d) from Sentinel-2 NDVI series for the island of Schiermonnikoog. The outer circle of the legend represents the first 10-day period of each month.
data point in November or December resulted in a relatively large RMSD. Excluding images in spring months (March to June) resulted in RMSD values for SOS-measures of < 5.0, suggesting that if part of the spring season would have above-normal cloud cover, the effect on SOS remains within limits. This can be attributed to the fact that the green-up phase (from minimum to maximum NDVI) usually takes place over a period of at least two months in the natural salt marsh areas (Fig. 3). However, when green-up is more rapid, like on agricultural plots or in semi-arid rangeland systems, missing a month of data may have a stronger effect.

5. Discussion

Our analysis showed that the retrieval of vegetation phenology at fine spatial resolution is possible with frequent Sentinel-2 imagery. Our NDVI-based retrievals were on average within 10 days of in-situ GCC.

<table>
<thead>
<tr>
<th>Vegetation community</th>
<th>SOS50</th>
<th>SOS50</th>
<th>PS90</th>
<th>EOS50</th>
<th>r</th>
<th>MSD</th>
<th>RMSD</th>
<th>#images</th>
<th>%pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dd: dry dunes</td>
<td>107±19</td>
<td>127±19</td>
<td>157±27</td>
<td>316±22</td>
<td>0.84</td>
<td>0.017</td>
<td>0.073</td>
<td>28.1</td>
<td>94.5</td>
</tr>
<tr>
<td>Ddk: dune mosaic</td>
<td>104±24</td>
<td>130±25</td>
<td>169±29</td>
<td>327±12</td>
<td>0.91</td>
<td>0.013</td>
<td>0.060</td>
<td>28.2</td>
<td>92.1</td>
</tr>
<tr>
<td>Dv: humid dunes</td>
<td>114±18</td>
<td>132±17</td>
<td>157±22</td>
<td>308±22</td>
<td>0.88</td>
<td>0.017</td>
<td>0.072</td>
<td>27.8</td>
<td>93.8</td>
</tr>
<tr>
<td>Kh: brackish marsh</td>
<td>112±19</td>
<td>136±18</td>
<td>170±20</td>
<td>312±23</td>
<td>0.92</td>
<td>0.015</td>
<td>0.062</td>
<td>27.7</td>
<td>95.8</td>
</tr>
<tr>
<td>Kh: high marsh</td>
<td>106±23</td>
<td>131±24</td>
<td>169±29</td>
<td>329±14</td>
<td>0.91</td>
<td>0.014</td>
<td>0.062</td>
<td>28.0</td>
<td>93.7</td>
</tr>
<tr>
<td>Km: middle-high marsh</td>
<td>102±16</td>
<td>124±17</td>
<td>158±21</td>
<td>325±15</td>
<td>0.92</td>
<td>0.015</td>
<td>0.068</td>
<td>27.8</td>
<td>98.5</td>
</tr>
<tr>
<td>Kl: low marsh</td>
<td>110±22</td>
<td>137±21</td>
<td>174±22</td>
<td>318±17</td>
<td>0.88</td>
<td>0.017</td>
<td>0.071</td>
<td>27.3</td>
<td>96.4</td>
</tr>
<tr>
<td>Kp: pioneer-zone marsh</td>
<td>132±47</td>
<td>159±41</td>
<td>198±38</td>
<td>338±26</td>
<td>0.82</td>
<td>0.020</td>
<td>0.082</td>
<td>25.4</td>
<td>72.2</td>
</tr>
<tr>
<td>Kpp: pre-pioneer-zone marsh</td>
<td>152±47</td>
<td>178±38</td>
<td>212±38</td>
<td>352±31</td>
<td>0.80</td>
<td>0.017</td>
<td>0.068</td>
<td>22.9</td>
<td>28.5</td>
</tr>
<tr>
<td>Gr: grassland</td>
<td>123±27</td>
<td>137±22</td>
<td>159±20</td>
<td>341±18</td>
<td>0.84</td>
<td>0.021</td>
<td>0.083</td>
<td>27.1</td>
<td>99.8</td>
</tr>
<tr>
<td>Ma: maize</td>
<td>174±21</td>
<td>185±13</td>
<td>200±6</td>
<td>284±15</td>
<td>0.92</td>
<td>0.024</td>
<td>0.109</td>
<td>26.8</td>
<td>99.9</td>
</tr>
<tr>
<td>Sv: beach and embryo dunes</td>
<td>166±67</td>
<td>198±66</td>
<td>238±71</td>
<td>357±30</td>
<td>0.80</td>
<td>0.014</td>
<td>0.053</td>
<td>27.6</td>
<td>1.1</td>
</tr>
<tr>
<td>All pixels island</td>
<td>111±28</td>
<td>133±26</td>
<td>165±30</td>
<td>321±24</td>
<td>0.87</td>
<td>0.017</td>
<td>0.072</td>
<td>27.6</td>
<td>77.5</td>
</tr>
</tbody>
</table>

Table 4 Summary statistics of the phenological retrievals from Sentinel-2 NDVI series for the entire island and per vegetation community (Fig. 1). Mean ± standard deviation are reported for the phenological parameters. Fit statistics (Pearson r, MSD, and RMSD) are calculated between fitted and original NDVI values; #images indicate the average number of Sentinel-2 observations used per fit, and %pixels specifies for what percentage of pixels within each class, a model could successfully be fitted. Per column, values are colour-coded from light (small) to dark (large).

Fig. 9. Difference (in days) between phenology parameters derived from Sentinel-2 NDVI and GCC series for SOS50 (a), SOS50 (b), PS90 (c), and EOS50 (d). Negatives mean that the NDVI series resulting in earlier dates than the GCC series.
retrievals of $S_{SO50}$ and $P_{SO50}$, while early green-up ($S_{SO20}$) and senescence ($E_{SO50}$) had an MSD of 19.0 and ~55.0 days, respectively (Fig. 5). The better correspondence between camera and fine-resolution satellite-retrievals for green-up than for senescence is in line with phenology studies in forest systems. For example, using multi-year Landsat analysis Nijland et al. (2016) reported an RMSE of 7 days for $S_{SO50}$ and 14 days for $E_{SO50}$ for mixed and coniferous forests in the Rocky Mountains. Similar findings were obtained by Melaas et al. (2016) for deciduous forest sites in North America.

Part of the deviation between phenology retrievals from NDVI, and GCCc can be explained by the use of different spectral indices. The exponential relationship (Fig. 6) makes that GCCc increases later in the green-up phase and stabilizes earlier in the decay phase, as compared to NDVI. GCCc-based phenology retrievals confirm these expected timing differences, but result only for $S_{SO50}$ and $E_{SO50}$ in a slightly stronger agreement with GCCc-based retrievals (Fig. 5). The exponential relationship also suggests that GCCc is more sensitive to higher biomass levels. This empirical finding is opposite to Wingate et al. (2015) who found that GCC was insensitive to LAI values above 2 based on a sensitivity analysis with PROSAIL, whereas NDVI remained sensitive for a wide range of LAI values.

An important difference between field camera and satellite observations is the viewing angle. Particularly the presence of a non-photosynthetic top layer (flowers, stems, seed heads) may reduce the visibility of green vegetation from an oblique view. Contrary to the proverb, we found that grass is not always greener on the other side of the fence. This effect applies to various periods in the phenological cycle (Moore et al., 1991), including during early vegetative growth due to presence of dead grasses and stems from the previous year (e.g., Liao et al., 2008; Ter Heerdt et al., 1991). Even if the top layer would be green, reflection in the visible bands is much affected at off-nadir viewing angles, as demonstrated for example for green wheat panicles (Zipoli and Grifont, 1994). As such, the sensor viewing angle affects spectral vegetation indices (e.g., Deering et al., 1992) and their temporal trajectory. The results of our two-layer radiative transfer model confirmed this dependency, even if the multiple vegetation components could at best be roughly represented in these models (see also Wenhan, 1993). By adding a top layer of vegetation with reduced chlorophyll content in our model, we could further explain observed differences between phenological parameters when retrieved from the camera versus satellite viewing geometry.

For the relatively inexpensive Bashnell cameras the spectral response function is not available and we could not adjust the automatic white balance and exposure. The use of more advanced camera systems for which the spectral response functions are known, could help in better characterizing the camera bands as input to radiative transfer modelling (Wingate et al., 2015). However, we did attempt replacing the Sentinel-2 spectral sensitivity with that from a Nikon RGB-camera, but found only minor differences in simulated GCCc values, suggesting little effect on the phenological results (data not shown). Their low cost allowed for installing multiple cameras in publicly-accessible sites without the need for additional security measures. Various studies have shown that cameras with different spectral responses and white balance settings resulted in similar phenological metrics (e.g., Mizunuma et al., 2013; Sonnentag et al., 2012; Zhao et al., 2012). Our study did highlight that viewing angle has an effect on the retrieval of phenological metrics. In this regard, camera systems observing at nadir could provide a stronger link with satellite recordings, although their observed area would be smaller compared to a tilted camera mounted at the same height above the canopy.

Despite differences between our satellite- and camera-based phenological retrievals, the density of Sentinel-2A observations allows extraction of phenological parameters with a consistent approach across the island at fine spatial resolution. Application of a consistent methodology can provide useful information on spatial patterns and inter-annual trends of phenology, even if literature suggests that phenological retrievals from satellite data remain typically within 10–30 days from visually-observed transition dates of individual plant species (White et al., 2014). This can partially be attributed to the occurrence of multiple species within a grid cell resulting in mixed spectra (Vrieling et al., 2017; Zhang et al., 2017). The finer spatial resolution of Sentinel-2 reduces this effect, as compared to medium-resolution series like MODIS. Nonetheless, most of the salt marsh is floristically diverse (Bockelmann et al., 2002; Pranger and Tolman, 2012), which implies that phenological metrics for 10 m grid cells still relate to the phenology of the vegetation community rather than of individual plants. Instead, for more uniform areas like cropland, Sentinel-2 retrievals can be related to the phenology of specific crop species, such as the timing of

---

Table 5

Impact of reduced image availability on NDVI-based phenology retrievals for the camera locations as compared to the full data set; #images indicates the average number of Sentinel-2 observations used per fit. The rows with the relative orbits indicate that only observations from that orbit were considered. The rows with individual months indicate that all observations for the indicated month were excluded from the retrieval. RMSD is colour-coded based on the overall minimum and maximum values (same for #images). MSD is colour-coded with blues indicating positive values (retrieved date for reduced data set is later than for the full data set) and red negatives.

<table>
<thead>
<tr>
<th>Reduced data set</th>
<th>#images</th>
<th>MSD</th>
<th>RMSD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative orbit 8</td>
<td>14.3</td>
<td>-5.7</td>
<td>-6.9</td>
</tr>
<tr>
<td>Relative orbit 51</td>
<td>13.4</td>
<td>-2.6</td>
<td>-1.5</td>
</tr>
<tr>
<td>January</td>
<td>26.9</td>
<td>-0.3</td>
<td>0.0</td>
</tr>
<tr>
<td>February</td>
<td>24.9</td>
<td>-0.8</td>
<td>-0.8</td>
</tr>
<tr>
<td>March</td>
<td>24.7</td>
<td>-1.2</td>
<td>-0.1</td>
</tr>
<tr>
<td>April</td>
<td>23.1</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td>May</td>
<td>24.7</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>June</td>
<td>26.7</td>
<td>-0.4</td>
<td>0.0</td>
</tr>
<tr>
<td>July</td>
<td>24.7</td>
<td>0.9</td>
<td>-0.7</td>
</tr>
<tr>
<td>August</td>
<td>25.4</td>
<td>3.4</td>
<td>2.2</td>
</tr>
<tr>
<td>September</td>
<td>24.1</td>
<td>-0.2</td>
<td>-0.1</td>
</tr>
<tr>
<td>October</td>
<td>25.9</td>
<td>-0.6</td>
<td>0.1</td>
</tr>
<tr>
<td>November</td>
<td>26.7</td>
<td>-0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>December</td>
<td>26.7</td>
<td>-0.2</td>
<td>-0.6</td>
</tr>
</tbody>
</table>
crop emergence (Claverie et al., 2012; Gao et al., 2017).

The phenological retrievals for the entire island revealed a large spatial variability (Fig. 8), confirming our earlier findings with 2015 imagery of RapidEye and SPOT5 (Vrieling et al., 2017). Similar to Vrieling et al. (2017), Fig. 8 shows very distinct and uniform phenological retrievals for the agricultural area (see also Fig. 1, Table 4). The natural vegetation communities reveal a greater heterogeneity, whereby pioneer-zone marshes generally green-up later than the higher marshes (see also Watkinson and Davy, 1985). The heterogeneity of phenology within natural classes may be partially explained by the large number of vegetation species with varying dominance with each vegetation community (Vrieling et al., 2017). The spatial patterns of the 2015 retrievals have a significant correlation with the 2016 Sentinel-2 retrievals with Pearson correlation coefficients of 0.47 for $\text{SO}_{40}$, 0.48 for $\text{SO}_{50}$ and 0.40 for $\text{PS}_{0}$, and MSD of 20.4, 19.3, and 18.4, respectively. The positive MSD indicates that retrieved dates were ~19 days later for 2015, which can be explained by the relatively cold spring that year. As such, the future build-up of an archive of short-interval Sentinel-2 imagery may assist in understanding varying phenological responses to weather patterns for heterogeneous vegetation communities.

Our study demonstrated that sufficient Sentinel-2 observations could be obtained for Schiermonnikoog to model the seasonal development of vegetation greenness throughout 2016; only a few gaps of more than one month occurred. Although we could benefit from overlapping orbits, the launch of Sentinel-2B in March 2017 resulted in the same repeat frequency globally, while increasing the frequency further towards the poles. Cloud cover may alter image availability depending on location and season. As a consequence, single-year phenology retrievals may not be successful always and everywhere, even if our study site experiences a medium-to-high cloud cover relative to other locations across the globe (King et al., 2013). We showed that a reduced image availability during a specific month can have varying effects depending on how that month is placed in the vegetation cycle, and that the effects may be small when sufficient other data points remain to describe the vegetation growth. Further enhancing image availability may require incorporating Landsat imagery (Wang et al., 2017), utilize dedicated missions for short-repeat observation of small targeted areas like Venüs (Dedieu et al., 2006), or using commercial constellations of many small satellites (Strauss, 2017). Nonetheless, we expect accurate single-year retrieval of phenology at fine resolution to become feasible for large parts of the globe using Sentinel-2 only.

6. Conclusions

We showed that phenological parameters can now be retrieved at 10 m resolution from Sentinel-2 image time series, providing new opportunities for landscape-scale phenology research. For areas with fine-scale spatial heterogeneity of vegetation communities, like Schiermonnikoog, Sentinel-2 allows retrieval and analysis of vegetation phenology with higher accuracy as compared to the commonly-used medium-resolution sensors like MODIS. Comparison of phenological parameters from satellite-derived NDVI series with camera-derived GCC series revealed that, despite their correlation, large differences existed between the two. We demonstrated that part of these differences could be explained by the vegetation index used and the different viewing angles for satellite and field camera. In general, spring green-up was closer spaced in time between the two sources as compared to timing of senescence. We argued that this may be partially affected by factors that are difficult to model like flowering and presence of non-photo-synthetic elements like grass seed heads, which are more dominant in the oblique camera view as compared to the closer to nadir satellite view. Two-layer radiative transfer modelling including a top layer with reduced chlorophyll concentrations could explain part of the observed differences due to viewing angle. Future investigation in other vegetation systems monitored by phenological cameras will allow to further appreciate Sentinel-2 and similar fine-resolution satellites as key tools for studying vegetation phenology.

Acknowledgements

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