



PhenoWin – An R Shiny application for visualization and extraction of phenological windows in Germany

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ABSTRACT

There is an increasing need for small scale information about the temporal shifting of the phenological crop development for applications like fertilization, irrigation, crop and soil protection, weather index insurance, yield prediction, crop classification or as bio-indicator of climate change. This application note introduces PhenoWin, a tool to extract and visualize phenological windows for any given year from 1993 onward and user-defined regions in Germany. Phenological windows represent successive start and end dates of development stages for different main crops, which have been interpolated using the phenological model PHASE. PhenoWin was implemented using R language and the R Shiny web framework. PhenoWin can be used as standalone application or can be embedded in web pages. Both, the used phenological data sets and the PhenoWin source code are available under open source license.

1. Introduction

Plant phenology describes annually and periodically reappearing stages in growth and development of plants, represented by clearly defined physiological events (Schmidt et al., 2014). In agriculture, the knowledge about the spatio-temporal characteristics of crop phenology is particularly important for applications such as timing of planting, fertilization, irrigation, crop and soil protection, yield prediction and weather index insurance (Bolton and Friedl, 2013; Chmielewski, 2003; Filella et al., 1995; Möller et al., 2017), crop classification (Bargiel, 2017; Foerster et al., 2012; Gerstmann et al., 2018; Heupel et al., 2018; Hu et al., 2019) or as bio-indicator of climate change and extreme weather assessment (Menzel et al., 2008; Fitchett et al., 2015; Dalhaus and Finger, 2016; Lüttger and Feike, 2018; Rezaei et al., Mar. 2018; Dalhaus et al., 2018; Möller et al., 2019; Vroege et al., 2019).

The monitoring of phenological events at national and regional scale by networks of volunteered observers has a long history and is conducted in several parts of the world¹ (Schwartz et al., 2003; Koch et al., 2010). Although the resulting “Volunteered Phenological Observations” (VPOs) can be characterized by inconsistencies (Mehdipour et al., 2015, 2018), they provide punctual and accurate information about specific phenological stages. Germany's national meteorological service DWD (Deutscher Wetterdienst) runs a phenological network of

yearly and immediate observers. About 1200 reporters observe and record 160 phenological phases of wild and cultivated plants. The observations are captured according to a standardized guideline, undergo an automatic quality assessment (Kaspar et al., 2014) and are available under an open data policy (Kaspar et al., 2019).

Phenological observations represent local information of an unknown scale-specific representativity (Möller and Volk, n.d.). Non-observed locations can be considered as spatial gaps (Grassini et al., 2015). They can be filled by applying spatial modelling techniques. Two groups can be distinguished: 1. The increased availability of satellite-based spectral vegetation index times series has led to the development of spatial modelling approaches characterizing the spatio-temporal development of “Land Surface Phenology” (LSP; Zeng et al., 2020). LSP metrics enable the detection of general annual vegetation changes including the start, peak and end of the annual growth season on regional or global scale. Limitations of LSP metrics are referred to satellite image processing and scale issues (Helman, 2018). A particular challenge lies in the relation of LSP metrics and physiological crop growth stages, which can only be partially implemented (Gao et al., 2017). 2. A more straightforward way is the application of regression and geostatistical interpolation algorithms on observations considering temporally environmental variables like elevation, slope or sunshine duration (Jeanneret et al., 2010). In contrast to LSP metrics, its

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¹ <https://www.usanpn.org/partner/gapon>.

application is spatially restricted to the extent of phenological observations. An example is the PHASE model, which was developed in order to provide historical spatial data sets of beginning growth stages (= phases) for the total area of Germany and main crop types (Gerstmann et al., 2016). As a result, the actual interpolated phase-specific “Days of the Year” (DOY) and a corresponding spatial accuracy metric is calculated, which expresses the pixel-specific standard error (Möller et al., 2019).

In this article, we introduce the Shiny application PhenoWin, which enables the visualization of successive crop-specific “Days of the Year” (DOYs) of beginning phases derived from PHASE modelling. In doing so, phenological windows can be extracted and compared for arbitrary dates and user-defined areas of interest (AOI) in Germany like administrative regions or agricultural objects such as field blocks or parcels (Inan et al., 2010).

2. Methodological background

The programming language R (R Core Team, 2018) is one of the most used open source software in data science (Lai et al., 2019). Since R includes packages to handle spatial geodata (e.g., sf, velox, raster; Hijmans and van Etten, 2012; Hunziker, 2017; Pebesma, 2018), spatial and statistical analysis can be efficiently coupled and visualized (Bivand et al., 2013). The application PhenoWin is mainly based on the Shiny package (Chang et al., 2019), which can be used to create web applications in R language. The packages leaflet and ggplot2 (Cheng et al., 2018; Wickham, 2016) are applied to manage interactive maps and draw plots. The Shiny package also provides web widgets, which allow to build links between web user interface (UI) and the server within one R file. Cascading style sheets (CSS) are used to arrange the widgets.

3. PhenoWin application

Fig. 1 shows the structure of the application, which can be divided into three parts:

- A A preprocessing routine converts all phenological raster datasets to R objects, which makes them accessible to the Shiny server (Subsection 3.1).
- B The Shiny server contains functions to create, display or download “Timeline Graps” or “Polar Graphs” of phenological windows (Subsection 3.2).
- C The Shiny user interface allows the user to define and change areas of interest, crop types or time ranges (sec. Subsection 3.3) and to plot graphs (Subsection 3.4).

Both, all used geodata sets of phenology and topography as well as the PhenoWin source code are available under open source license. The R source code, a subset of phenological data and the study’s test sites are hosted and documented on GitHub². The preprocessing routine can be started by executing `Extract_Geotif.R`³. The actual PhenoWin application is called by the file `Graph_Pheno.R`⁴.

3.1. Preprocessing

In Table 1, all considered raster data sets of beginning phenological phases are listed. The interpolations are based on continuous and complete yearly observations of six main crop types since 1993. At this time, a new Germany-wide observation program was established (Kaspar et al., 2014). The total data set includes 1188 raster

representing 44 phases and 27 years between 1993 and 2019. All raster files with the EPSG projection 31467⁵ follow the naming convention `DOY_[Crop ID]_[Phase ID]_[Year].tif` and can be downloaded with a geodata web interface⁶, which is updated regularly.

Applying functions of the raster and velox packages, crop-specific raster data sets are stacked (Hunziker, 2017). The resulting velox objects enable fast raster operations and are saved according to the naming convention `DOY_[Crop ID].rds`.

3.2. Shiny server

3.2.1. Spatial objects

The application’s interface enables the user to specify test sites. By using two widgets, spatial objects can be defined and uploaded:

- The `addDrawToolbar` function from the `leaflet.extra` package (Karambelkar and Schloerke, 2018) allows for the selection of points or polygons directly on the interactive map.
- GeoJSON files of spatial polygons or points can be uploaded using the `fileInput` function from the Shiny package (Chang et al., 2019).

The uploaded spatial objects are converted to “simple feature” (sf) objects by using the `st_read` function of the `sf` package (Pebesma, 2018). Since Leaflet requires WGS84 projection (EPSG code 4326)⁷, all inputs are reprojected accordingly.

3.2.2. Data processing

The selected sf objects are coupled with the input velox objects containing the phenological raster data. In case of polygons, values of the overlapping pixels are extracted. Spatial points are related to the values of the pixels, in which they are situated.

3.3. Shiny user interface

The interface is divided into three parts. Its usage is explained based on the example of a parcel situated in Central Germany and its corresponding administrative district (Figs. 2 and 4):

1. The header window combines several configuration options, which can be set or adjusted:
 - The “Select Crop” drop-down list summarizes all crop types, for which pre-processed phenological phases are available (see Subsection 3.1) and phenological windows can be shown. The list is based on the editable text file `crops.csv`⁸, which is part of the PhenoWin GitHub project. The corresponding phases are defined in the editable text file `Phases.csv`⁹. There, the phase-specific color codes can also be supplemented or changed.
 - The “Import GeoJSON” browser button activates a window to import one or more test site points or polygons in GeoJSON format in any projection.
 - There are two interaction modes for test sites: the “Select” mode allows their selection or deselection for plotting graphs, which is indicated by transparent red and blue polygon colors. In the “Delete” mode, test sites can be removed.
 - After defining the crop type and importing, picking or drawing and selecting one or more test site(s), clicking on the “Draw Graph” button results in one or more output graph(s) (Subsection 3.4). By default, a “Timeline Graph” is plotted (Subsection 3.4.1).

⁵ <https://spatialreference.org/ref/epsg/31467/>.

⁶ <http://synops.julius-kuehn.de/phaenophase/>.

⁷ <https://spatialreference.org/ref/epsg/wgs-84/>.

⁸ <https://github.com/EMRAgit/PhenoWin/blob/master/crops.csv>.

⁹ <https://github.com/EMRAgit/PhenoWin/blob/master/Phases.csv>.

² <https://github.com/EMRAgit/PhenoWin>.

³ https://github.com/EMRAgit/PhenoWin/blob/master/Extract_Geotif.R.

⁴ https://github.com/EMRAgit/PhenoWin/blob/master/Graph_Pheno.R.

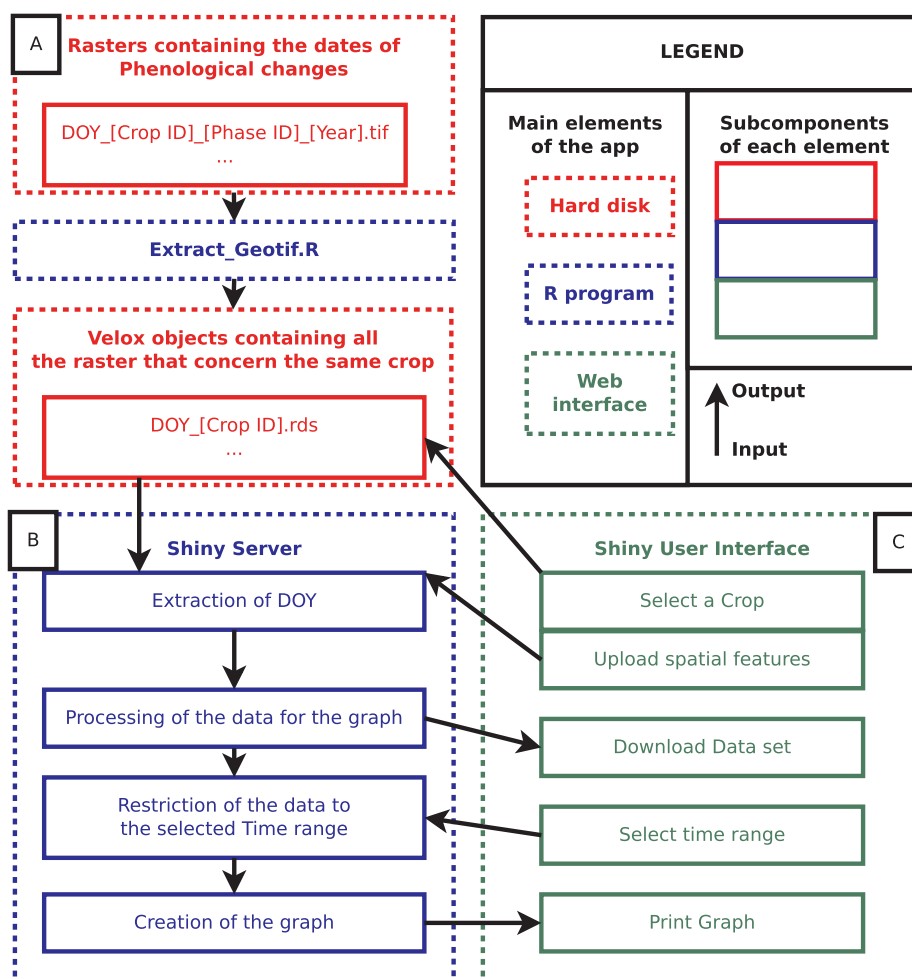


Fig. 1. PhenoWin structure.

Table 1

Interpolated crop-specific and Germany-wide phenological phases for the period between 1993 and 2018. Crop codes: 201 – perennial grassland | 202 – winter wheat | 204 – winter barley | 205 – winter rape | 208 – summer oats | 215 – corn | 253 – sugar beet. PHASE codes: 1 – beginning of turning green | 5 – beginning of flowering | 10 – sowing | 12 – emergence | 13 – closed stand | 14 – 4th leaf unfolded | 15/67 – shooting/stem elongation | 17 – bud formation | 18/66 – heading/tassel emergence | 19 – milk ripening | 20 – early dough ripening | 21 – yellow ripening | 22 – full ripening | 24 – harvest | 25 – 1st cut for hay | 26 – 1st cut for silage | 65 – tassel emergence.

PHASES	201	202	204	205	208	215	253
1	•						
5				•		•	
10		•	•	•	•	•	•
12		•	•	•	•	•	•
13							•
14				•			
15		•	•		•		
17				•			
18		•	•				
19		•			•	•	
20						•	
21		•	•		•	•	
22				•			
24		•	•	•	•	•	•
25	•						
26	•						
65						•	
66					•		
67				•		•	

Activating a checkbox, a “Polar Graph” is displayed (Subsection 3.4.2). The total height of the output graph can be varied by a “Graph Height” slider. This option can be useful if two or more test sites should be compared.

- The total test site-specific data sets and corresponding polygons or points can be downloaded as text file (button “Download Extracted Dataset”) and in GeoJSON format (button “Export GeoJSON”), respectively.
 - Pressing the “Download Phase Code” button provides a text file, where the phase codes and their names as well as their associated color codes are listed.
2. Maps are displayed by applying functions of the `leaflet` package (Cheng et al., 2018) and contain standard functions like “zoom in” or “zoom out”, and a search option based on the open street map geocoder. The user can also add interactively test site points or polygons within the map. The map background can be set by WMSs of OpenStreetMap¹⁰, OpenTopoMap¹¹ or Orthophotos from the ESRI World Imagery¹². Figs. 2a and 4a show the polygons of the district of Mansfeld-Südharz (DEE0C) and the test parcel (DESTLI0500950004), which were imported using the “Import GeoJSON” option. The map’s background is defined by Open-TopoMap WMS.

¹⁰ <https://www.openstreetmap.org>.

¹¹ <https://opentopomap.org>.

¹² https://services.arcgisonline.com/ArcGIS/rest/services/World_Imagery/MapServer

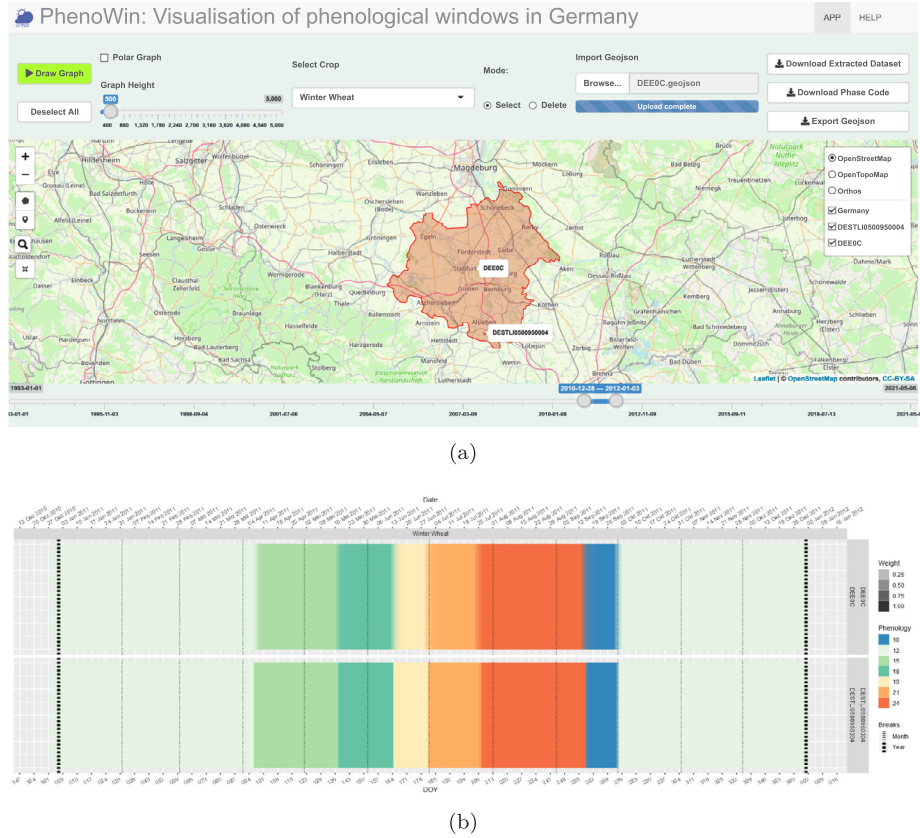


Fig. 2. PhenoWin User Interface (a) and two timeline graphs (b) derived for a parcel (DESTLI0500950004) and its corresponding administrative district (DEE0C), winter wheat and the period between 28th December 2010 and 3rd January 2012. The dotted lines indicate the end of a month or year.

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	1	1
0	0	0	1	1	1
0	0	0	1	1	1
0	0	1	1	1	1

Fig. 3. Illustration of a DOY-specific phase transition zone: the red line indicates an area of interest (AOI), the red pixels are associated with the corresponding polygon. The values 0 and 1 represent pixels with a correct and incorrect chronological phase sequence.

3. The time period selector allows to set temporal limits of the graph. They are valid for all selected test sites. The temporal range of the selector is related to the available (and expandable) phenological data sets, which is the result of the preprocessing routine (Subsection 3.1).

3.4. Output graphs

The output graphs result from applying functions of the *ggplot2* package (Wickham, 2016). Each color corresponds to a phenological phase. Green colors refer to vital phases like “emergence” or “shooting”, and yellowish or orange colors indicate ripening phases.

3.4.1. Timeline graphs

Fig. 2 displays the PhenoWin User Interface. Two polygons of a parcel (DESTLI0500950004) and its administrative district (DEE0C) are imported and active. For both AOIs, the crop type “winter wheat” and the period between 28th December 2010 and 3rd January 2012, two

timeline graphs are simultaneously derived. They display the chronological sequence of beginning phenological phases on a timescale in DOYs and dates.

The comparison of both timeline graphs reveal similar patterns. However, the timeline graph of the administrative district (DEE0C) is characterized by blurry phase transition zones. This phenomenon reflects the heterogeneity of larger areas as well as observation or interpolation inaccuracies (see Gerstmann et al., 2016). As a consequence, on DOYs in the temporal transitional range between two following phases, the second phase (e.g., shooting) can occur earlier than the first phase (e.g., emerging). This is illustrated in Fig. 3, where a red colored AOI contains four pixels with an incorrect and nine pixels with a correct chronological sequence. The correct and incorrect pixels are flagged by the values “0” and “1”. The ratio of the number of correct pixels ($PN_{DOY}^{AOI,0}$) and the total pixel number associated with the AOI (PN^{AOI}) results in a test site- and DOY-specific weighting factor W_{DOY} (Eq. 1). The example of Fig. 3 gives a weighting factor of $W_{DOY} = 9/13 = 0.69$.

$$W_{DOY} = \frac{PN_{DOY}^{AOI,0}}{PN^{AOI}} \quad (1)$$

As illustrated in the grey legend of the output graph, the weighting factor controls the opacity of the phase colors. This means for the actual output graph, that such temporal windows of uncertain phase data are visualized by overlapping phase colours of specific opacity degrees. This is visible in the DEE0C graph, for instance, between the phases 18 (heading) and 21 (yellow ripeness; Fig. 2b).

3.4.2. Polar graphs

Fig. 4 shows a polar graph, where the start of the x axis is centered at the midpoint of a plot frame on a 0:360° circle. In doing so, several years of a test site and crop type can be compared regarding their inter-annual differences of beginning phases, which enables the



Fig. 4. PhenoWin User Interface (a) and polar graph (b) derived for a parcel (DESTLI0500950004), maize and the period between 1st January 2010 and 27th December 2019.

identification of uncommon plant development situations. Here, the sequences of maize between 3rd January 2010 and 27th December 2019 are compared for the example parcel (DESTLI0500950004) and the crop type maize. Accordingly, the early development of all phases in 2018 can be made visible, which was caused by high temperatures in spring.

4. Conclusion and outlook

There is an increasing need for information about the temporal shifting of the phenological crop development. This study is based on a Germany-wide spatial gridded data base, which results from interpolated observations of beginning phases and represents the spatio-temporal variability of phenological crop development of the entire territory of Germany. In this context, the PhenoWin application aims at the visualization of phenological windows for user-defined AOIs and time periods. In doing so, different test sites and years can be compared regarding its crop-specific phenological development.

PhenoWin can be used as standalone application or can be embedded in web pages. The programming R language has been proven as a suitable environment to combine efficiently spatial data set operations (packages *velox* and *sf*) with web-related visualization techniques (Shiny package).

The PhenoWin application can be considered as a contribution to make geodata, findable, accessible, interoperable and reusable (FAIR; Evans et al., 2017). A further step in this context would be the integration of spatial accuracy information, which are available for all used phenological data in this study (Gerstmann et al., 2016; Möller et al., 2019). This could support the trustworthiness of the shown data (Dalhaus and Finger, 2016; Lokers et al., 2016). Our presented approach of open data and source code can promote further developments in the agricultural context, where dynamic phenological information are required. This concerns, for example, extreme weather assessment or soil erosion modelling (Möller et al., 2017; Möller et al., 2019). The presented approach is also suitable to visualize other similar spatial geodata like phenological metrics derived from remote sensing imagery (Araya et al., 2018; Jönsson and Eklundh, 2004; Rodrigues et al., 2013).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRedit authorship contribution statement

Markus Möller: Conceptualization, Methodology, Data curation.
Lucas Boutarfa: Software, Methodology. **Jörn Strassmeyer:**
 Supervision, Writing - review & editing.

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