Using satellite imagery and ground observations to quantify the effect of intra-annually changing temperature patterns on spring time phenology

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Introduction

The phenological evolution of deciduous trees in spring time is predominantly determined by daily mean temperature patterns. These patterns vary considerably from year to year. Thus, one can observe a variety of different temporal evolutions. We analysed and modelled the relationship of anomalies in temperature and their effect on the phenological pace. We have done so by firstly comparing green-up days derived from satellite images with the number of budburst dates for different tree species detected with phenological ground observations. Secondly, the relationship between the evolution of daily mean temperatures and of observed budburst dates during springtime was explored. The spatial correlation of phenological time series was also analysed in order to investigate intra-regional and inter-regional variance of budburst.

Material and Methods

The NDVI green-up signal of AVHRR images from 1989–1998. Phenological ground observations of the German Weather Service from 1951-2000.

The frequency distributions of observed budburst dates were modelled by applying Gaussian Mixtures Models. The mixture components could be identified either via expectation-maximisation (EM) or via an optimisation algorithm.

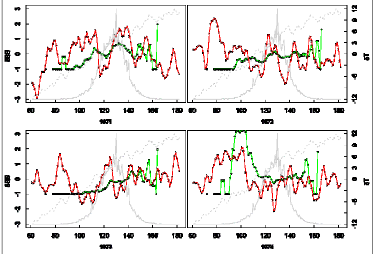
The satellite pixels were classified on basis of a land use map for Europe at 1 km resolution (CORINE)

To visualise a distinctive behaviour of Natural Regions we used Time-Geographical Methods (Multidimensional Scaling).

Temperature anomalies affect the phenological pace

Calculation of the Grand Mean of daily mean temperatures (*grey dashed* line) and number of stations with observed onset of budburst per day (BB) of Oak in spring time (*grey thick* line) from 1951-2000. The anomalies of daily mean temperatures (*red* line, δT) and number of stations which recorded budburst (*green* line, δBB) relative to their Grand Means are shown below. Here we analysed the years 1971-1974.

The pace of phenological development reacts with a slight delay on positive temperature anomalies and vice versa.

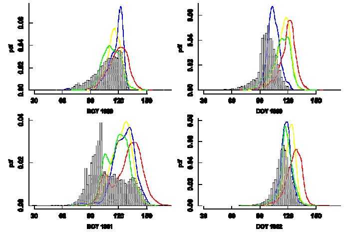


NDVI vs ground observations

We then compared the probability density function of satellite pixels which intersect with deciduous forest (*grey* bars) with the density functions of ground observations for Beech (*green* line) and Oak (*red* line).

Furthermore, only those NDVI pixels were selected for comparison, of which the mid-point was inside a 0.25 × 0.25 km CORINE deciduous forest pixel that was surrounded by at least three rows of deciduous forest pixels on any side. Thus, the NDVI pixel was buffered by *ca.* 0.375 km of deciduous forests to be included in the comparison.

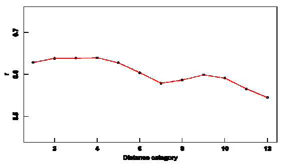
The correspondent density function (*blue* line) resembles a computed mixture of Beech and Oak (*yellow* line). Hence, focussing on NDVI pixels which observe pure deciduous forest leads to improved results. Here, the findings for the years 1989-1992 are shown.



Spatial correlation of phenological time series

Each observation was correlated with every other station provided both had records of at least 30 identical years. Dependent on the distance between the station pair the computed correlation was assigned to a distance category. First results showed only weak correlation of *r = 0.42*.

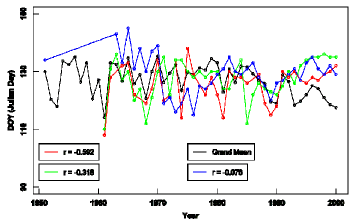
Consequently, we constrained the cases when observation pairs were compared such that only years showing a unimodal frequency distribution were included in the analysis. Now, we determined a correlation of *r = 0.61*. Although further apart, remote observation pairs are nearly as strongly correlated as neighbouring pairs.



Distance categories in [km] 0-25, 25-50, 50-75, 75-100, 100-200, 200-300, 300-400, 400-500, 500-600, 600-700, 700-800, 800-900

We then focused on observation stations which show negative correlations over all distance categories. This dissimilar temporal behaviour can potentially be caused by a change of the observer, a change of observed object, changes within the immediate environment of the observed object or observation of the wrong phenological phase. The figure below illustrates the records of observations stations (*red*, *blue* and *green* line) with negative mean correlations and the Grand Mean (*black* line) budburst date.

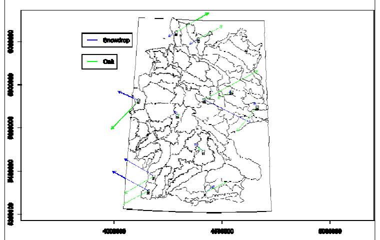
This is a potential tool to identify time series which show a change in regime or a inversed trend.



Time-Geographical Visualisation

Multidimensional Scaling was applied such that dissimilarities of the observations were reflected within a 2-dimensional space. Input data: XY-coordinates and the Natural Regions relative position in terms of an early onset of a phenological phase.

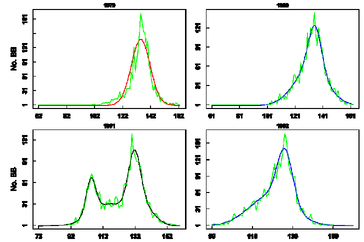
The flowering of Snowdrop (*blue* arrows) and the budburst of Oak (*green* arrows) were analysed. We found that regions in the Southwest showed similar behaviour for both phases. The coastal regions in the North are much more dissimilar for Oak than for Snowdrop when compared to the Southwest. Regions in the middle of Germany are intermediate between the extremes in terms of an early or late onset. The natural region *38* shows extreme behaviour as it consists of a mountainous area.



Characterisation of the temporal evolution using Gaussian Mixtures

The EM algorithm was initialised by hierarchical clustering for parameterised Gaussian Mixture models. The number of clusters and the clustering model is chosen to maximise the Bayesian Information Criterion (BIC). Secondly, an optimisation algorithm was applied on the minimisation of several (maximum four) Gaussian Mixture functions. Based on Akaike's Information criterion it was decided which optimised function was the most appropriate. The graphs below show the frequency distributions of Oak (green line) from 1978-1982 with the julian day on the *x-axis*. The number of mixture components is indicated by colour of the fitted line: *red* = one component, *blue* = two components, *grey* = three components and *black* = four components.

Most of the observed frequency distribution could be fitted reasonable well with both methodologies. In some cases however, the EM-algorithm would perform better and the other way around. The underlying cause could yet not be identified.



Conclusions

The computed green-up date based on NDVI values is hugely dependent on the mixture of the observed underlying components. By buffering the NDVI pixels one takes into account the satellites geometrical fuzziness and thereby obtains results closer to actual ground observations.

The pace of phenological development during spring time responds rapidly to changing weather conditions, i.e. a cold spell.

Phenological observations are relatively strongly correlated even over large distances. Low temporal correlations are mainly due to years which reflect strongly discontinuous weather patterns.

MDS can provide a useful tool to easily visualise emergent behaviour of spatio-temporal processes.

Glossary

NDVI = Normalized Difference Vegetation Index

AVHRR = Advanced Very High Resolution Radiometer

CORINE = Coordinated Information on the European Environment; land cover set

DOY = Day Of Year