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Development and analysis of spring plant phenology products: 36 years of 1-km grids over the conterminous US

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ABSTRACT

Time series of phenological products provide information on the timings of recurrent biological events and on their temporal trends. This information is key to studying the impacts of climate change on our planet as well as for managing natural resources and agricultural production. Here we develop and analyze new long term phenological products: 1 km grids of the Extended Spring Indices (SI-x) over the conterminous United States from 1980 to 2015. These new products (based on Daymet daily temperature grids and created by using cloud computing) allow the analysis of two primary variables (first leaf and first bloom) and two derivative products (Damage Index and Last Freeze Day) at a much finer spatial resolution than previous gridded or interpolated products. Furthermore, our products provide enough temporal depth to reliably analyze trends and changes in the timing of spring arrival at continental scales. Validation results confirm that our products largely agree with lilac and honeysuckle leaf and flowering onset observations. The spatial analysis shows a significantly delayed spring onset in the northern US whereas in the western and the Great Lakes region, spring onset advances. The mean temporal variabilities of the indices were analyzed for the nine major climatic regions of the US and results showed a clear division into three main groups: early, average and late spring onset. Finally, the region belonging to each group was mapped. These examples show the potential of our four phenological products to improve understanding of the responses of ecosystems to a changing climate.

1. Introduction

Changes in climate are evident in observational weather and ecological records (Kerr and Ostrovsky, 2003). According to the Intergovernmental Panel on Climate Change (IPCC), there is strong evidence that human activities are behind most of these changes. A tangible impact of these modifications is the increasing frequency of temperature extremes. The spatial and temporal variability of temperature has a direct impact on the timing of recurrent biological events of plants and animals (bird migrations (Cohen et al., 2018), early appearance or early flowering of the plants (Thomson, 2010), for example). This, in turn, has a direct impact on land surface–atmosphere interactions and associated biogeochemical cycles. Therefore, it is essential to understand how terrestrial ecosystems are responding to climate change (Richardson et al., 2013). In recent decades, climate change research has increasingly involved remote sensing technologies (Rosenqvist et al., 2003) using satellite images to derive land surface phenology and in situ measurements provided by weather stations. The former overcome interpolation problems but the latter supply measurements that are easier to relate to ground processes and observations (Mendelsohn et al., 2007). Satellite, airborne and meteorological sensors provide observations of the Earth's surface at global, regional and, local scales. All these measures are used to derive products to study the impact of climate change on our planet (Broich et al., 2015; Villoria et al., 2016).

Consistent climate change indicators are needed to better understand the different causes and impacts of climate change on our ecosystems. Phenological observations constitute one of the most sensitive indicators of climate change (Parry et al., 2007) because they contain information about the timing of recurrent biological events that are strongly linked to the local weather and climate of the area. Various phenological indicators have been derived using phenological models (Tucker, 1979; Glibert et al., 2014). The simplest phenological models are Thermal Time models (Linkosalo et al., 2008). Among several meteorologically based measures of thermal time, Growing Degree Day

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(GDD) is suitable for modelling plant growth (Shaykewich, 1995). GDD is the basis of the Extended Spring Indices models (SI-x) (Schwartz, 1985; Ault et al., 2015b). The SI-x models are used to generate a *Start of Spring* indicator[2] which is included in the US Global Change Research Program. The *Start of Spring* indicator uses the accumulation of heat to predict the day of the year on which temperature-sensitive plans leaf out and start blooming. *Start of Spring* provides a direct connection between vegetation phenology effects and global warming.

Different studies have used the SI-x models to analyze variations in spring onset linked to climate change (Schwartz et al., 2013; Allstadt et al., 2015). Most of these studies are based on plant and weather observations stations at specific locations (Ault et al., 2013, 2015b) but current work broadens the analyses to gridded SI-x products. Originally available at relatively coarse spatial resolutions (1° (Ault et al., 2015a) and 25 km (Wu et al., 2016)) and more recently at resolutions of about 15 (Allstadt et al., 2015) and 4 km (Crimmins et al., 2017), from which a resampled 2 km product is also derived.[3] High spatial resolution SI-x products have special relevance in highly variable territories such as North America, which present multiple and complex topographies. Thus, high spatial resolution phenological products could be used to obtain more realistic views of local phenology and to support regional ecological studies. Additionally, having long time series of high spatial resolution products helps to avoid drawing misleading conclusions based on short-term conditions and/or trends (Cohen et al., 2018).

Until now, technology has limited high spatial resolution phenological modeling to small areas due to the huge quantity of data that had to be processed. However, the advancement of Information and Communications Technologies (ICT) allows not only the visualization and analysis of climate data (Zhang et al., 2016; Arundel et al., 2016; Bradley et al., 2010) but also the development of new SI-x products using cloud computing (Broich et al., 2015). The increasing accessibility and lower costs of cloud computing have made it possible to study geographic phenomena at high spatial resolution, over long periods of time, and at continental to global scales. One example of an easily accessible and free cloud computing application is Google Earth Engine. This application is based on the well-known map-reduce paradigm introduced by Google,[4] which considerably speed up data processing and helps to scale up the required computations (Gorelick et al., 2017).

In this paper we present new spring onset gridded products based on the SI-x models. Our products, available at 1 km and for the period 1980–2015, consist of four variables (two primary, one observational and one derived; c.f. Section 2). The primary products are verified, validated and analyzed to evaluate their quality and to check their consistency with previous SI-x products and studies. Our analysis focuses on studying spatio-temporal patterns of spring onset, mapping trends and on the use of the SI-x to regionalize the conterminous US.

2. The Extended Spring Indices

The Extended Spring Indices (SI-x) are a suite of models developed by Schwartz et al. (2013) by removing the chilling requirements from the original of spring indices models (Schwartz, 1997). This allows the SI-x to have a wider geographic applicability and to model spring onset for the complete conterminous US (CONUS). The SI-x models are primary used to predict “Leaf” (LF) and “Bloom” (BL) indices for three indicator plant species (Lilac (*Syringa chinensis “Red Rothomagensis”*)) and Honeysuckle (*Lonicera tatarica “Arnold Red” and Lonicera korolkowii “Zabeli”*)).

The SI-x models are based on Growing Degree Hours (GDH), which are calculated from daily minimum and maximum temperatures. These GDH are used to define accumulation of short- and long-term variables. These variable are used in regression based models that predict LF and BL for each plant species. The regression coefficients were calculated by Schwartz et al. (2013):

- The LF index is the average of the first day of the year that fulfills:

$$\begin{aligned} &DDE2*0.201 + DD57*0.153 + SYNOP*3.306 + MDS0 *13.878 >= 1000(\text{Lilac}) \\ &DD57*0.248 + SYNOP*4.266 + MDS0 *20.899 >= 1000(\text{Arnold Red Honeysuckle}) \\ &DDE2*0.266 + SYNOP*2.802 + MDS0 *21.433 >= 1000(\text{Zabeli Honeysuckle}), \end{aligned} \quad (1)$$

  where $DDE2$ is the accumulated GDH from day t until day $t+2$, $DD57$ is the accumulated GDH from day $t+5$ until day $t+7$ with t being a temporal index from January 1st, $ASYNOP$ is accumulative of the synop variable which is 1 when $DDE2 > 637$ and otherwise is 0 and $MDS0$ is a counter that starts on January 1st.
- Likewise, the BL index is obtained by averaging the first day of the year that fulfills:

$$\begin{aligned} &ACGDH*0.116 - MDS0*23.934 >= 1000(\text{Lilac}) \\ &ACGDH*0.127 - MDS0*24.825 >= 1000(\text{Arnold Red Honeysuckle}) \\ &ACGDH*0.096 - MDS0*11.368 >= 1000(\text{Zabeli Honeysuckle}). \end{aligned} \quad (2)$$

  In this case, $ACGDH$ is the accumulation of GDH from LF index and, $MDS0$ is still a counter but it starts on the LF index date.

The SI-x models are not limited to predicting just these primary indices. The SI-x also output two derivative products: Last Freeze (LSF) and Damage Index (DI). The LSF is the last day of the year whose minimum temperature is lower than or equal to 28° F (∼ −2.22° C). The DI links the LF index and LSF to measure the risk of frost damage. That risk is quantified by the difference between the anomalies of LF index and the LSF. Thus, very negative DI values indicate a high probability of frost damage. For more information on the SI-x models see Ault et al. (2015b), Schwartz et al. (2006).

3. Scaling up the Spring Index models

The Google Earth Engine (GEE) platform was chosen to scale up the calculation of the SI-x models. GEE[5] is a free and cloud-based application that specializes in geospatial processing. However, GEE cannot run the original Fortran and Matlab codes (Ault et al., 2015b) so these had to be restructured to exploit the parallel processing environment of the cloud. In this section, we first describe the data used in this work, then the restructuration of the model to cloud computing, and finally, the process of verifying, validating and analyzing.

3.1. Data

The data belongs to two main groups: the data used to obtain the SI-x products at 1 km (environmental data) and the data applied in the evaluation and analysis of the products (ancillary data).

- Environmental data:
  Daily surface weather data (Daymet) version 2 is available in GEE. Daymet is a continuous surface dataset available at a spatial resolution of 1 km for the CONUS (Thornton et al., 2014). Daymet data is available between January 1st, 1980 and January 1st, 2016 and it covers the following spatial range: latitudes between 10 and 53° and longitudes between −133.5 and −49.9°. This means that

[2] http://www.globalchange.gov/explore/indicators.
[3] https://www.usanpn.org/data/spring_indices.
[4] https://developers.google.com/earth-engine/.
[5] https://developers.google.com/earth-engine/.