Continental-Scale Monitoring and Mapping of False Spring: A Cloud Computing Solution

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Abstract

Global warming has shifted the onset of spring plant phenology towards earlier dates. This shift can lead to “false springs” (plants get frost damage) because the date of last frost has not advanced at the same pace than the advancement of spring onset. Here, we use a cloud computing approach for processing big and high spatial resolution grids of temperature data to map the occurrence of false springs and to study their temporal trends. We demonstrate our approach using Daymet, which provides daily weather data at 1km for continental US, and the extended spring indices models. Results show that the risk of having false springs is high in the Midwest and in Northeast of the US. This extensive regional variation highlights the necessity of continuous monitoring and mapping of false spring.

Keywords: Cloud computing, Spatio-temporal models, Big Data, Phenology, False Spring.

1. Introduction

The increase in global temperature has resulted in earlier onsets of spring plant growth (Schwartz et al. 2006). However, the rate of change of last frosts has not advanced at the same pace and this mismatch has led to the occurrence of “false springs” (i.e. springs where plants get frost damage (Knudson 2012)). False springs affect both natural and agricultural systems because frost damage can reduce plant productivity and, as a result, can have a negative impact on the dependent animal populations (Augspurger 2013). For instance, the agricultural damage caused by the false spring of 2012 was estimated in 500$ millions only in the state of Michigan (Ault et al. 2013; Knudson 2012). Thus, the study of false springs is key to understanding the ecological and financial impact of climate change on terrestrial ecosystems.

Phenology is the science that studies periodic plant and animal life cycle events and how seasonal and inter-annual weather and climate variations affect them. Plants in mid-latitudes such as in US are particularly responsive to temperature variations in the spring season (Schwartz 1999). Hence, phenological models addressing spring phenology are extremely useful for monitoring false springs. These models can be used to predict the timing of phenological events, including the onset of spring. For example, the extended spring indices (SI-x) are a suite of phenological models widely used to predict spring phenology (Allstadt et al. 2015; Izquierdo-Verdiguier et al. 2017). Although the SI-x were calibrated to predict the day of the year (DOY) of first leaf and bloom for lilacs and honeysuckle, these models have proven their usefulness to predict spring onset. This is because the timing of first leaf and first bloom for these species are highly correlated with other natural and agricultural events (Schwartz et al. 2013).

The SI-x models use daily minimum and maximum temperatures to predict the DOY of two primary variables (First Leaf and First Bloom) and two derivative products (DOY of Last Frost and Damage Index). The availability of these meteorological variables at fine spatial resolutions and over long periods of time provides a unique opportunity to study the spatial and temporal patterns of the false springs. However, limitations in processing power have hampered the production of these geo-information products at continental scales.

This paper proposes a cloud-based approach for processing time series of high spatial resolution grids of weather data using a phenological model that can be used to identify the occurrence of false springs. In particular, we explore and demonstrate a well-known cloud computing solution to calculate and map false spring over continental US using the SI-x and Daymet weather dataset.

2. Materials and methods

We used Daymet (Thornton et al. 1997), a daily weather dataset, to calculate spring onset dates with the SI-x models and to map the occurrence of false springs over continental US. Daymet provides gridded data at 1km and since 1980. These characteristics made a suitable dataset to analyse the spatial and temporal patterns of false springs at continental scales. For this study, we processed Daymet minimum and maximum temperature and day length data for the period 1980-2015. The total size of this data was about 630 GB.

Cloud computing solutions provide on demand shared computer processing resources and access to big datasets. For this study, we used Google Earth Engine[1] (GEE), a specialized cloud computing platform for geospatial processing. GEE contains a data catalogue that includes satellite images as well as other gridded datasets like Daymet. We used the python application programming interface of GEE (GEE-API) to generate yearly maps of the damage index, which records the anomalous number of days between the DOY of first leaf and DOY of the last day whose minimum temperature drops below -2.2 degree Celsius (Allstadt et al. 2015).

We used a linear regression to model the trend in damage index over the complete study period to understand and map the impact of climate change in the US. We also generated yearly binary maps of false spring. These maps take the value 1 if the DOY of the last freeze occurred during within seven days after the DOY of first leaf and the value 0 otherwise. Finally, we also calculated the mean of the damage index anomalies and of the false springs for the complete study period.

3. Results and Discussion

Figure 1 illustrates the average damage index anomalies from 1980 to 2015 and shows that the variability of last freezing ranges from about 10 days before to 10 days after the DOY of the first leaf. The areas with negative values are areas where first leaf tends to occur after the last freeze. These areas often do not experience freezing weather such as the Gulf and the West Coasts and the Southwest. Or, they are areas where phenology is mostly driven by photoperiod (e.g., upper Midwest, Western New York). In areas with positive values the first leaf frequently occurs before the last freeze (e.g., North Central and Rockies, Central/Midwest).

1 https://developers.google.com/earth-engine/

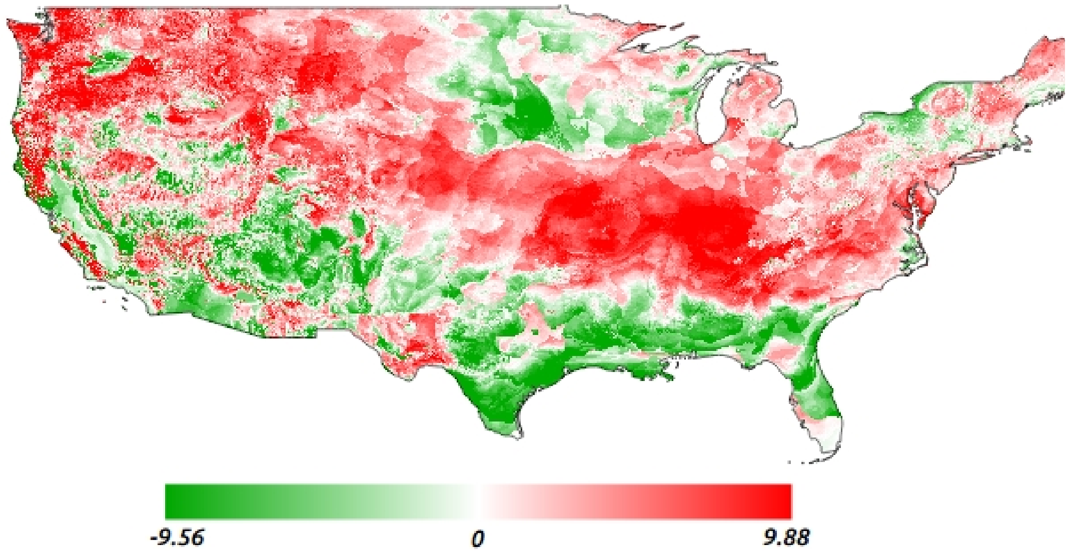

Figure 1: The average difference between DOY of first leaf and last freeze from 1980 to 2015.

Figure 2 shows the temporal trend of damage index for the period 1980 to 2015. Increase in damage index were very common throughout much of the region, occurring almost at all locations. However, the increase was larger in certain high elevation areas and southern US than the rest of the US. The positive values in the trend of damage index are concentrated in the Great Plains due to either early last freeze dates or late first leaf dates. The areas coloured in white have similar damage index anomalies over the complete study period (i.e., no temporal trend in damage index values).

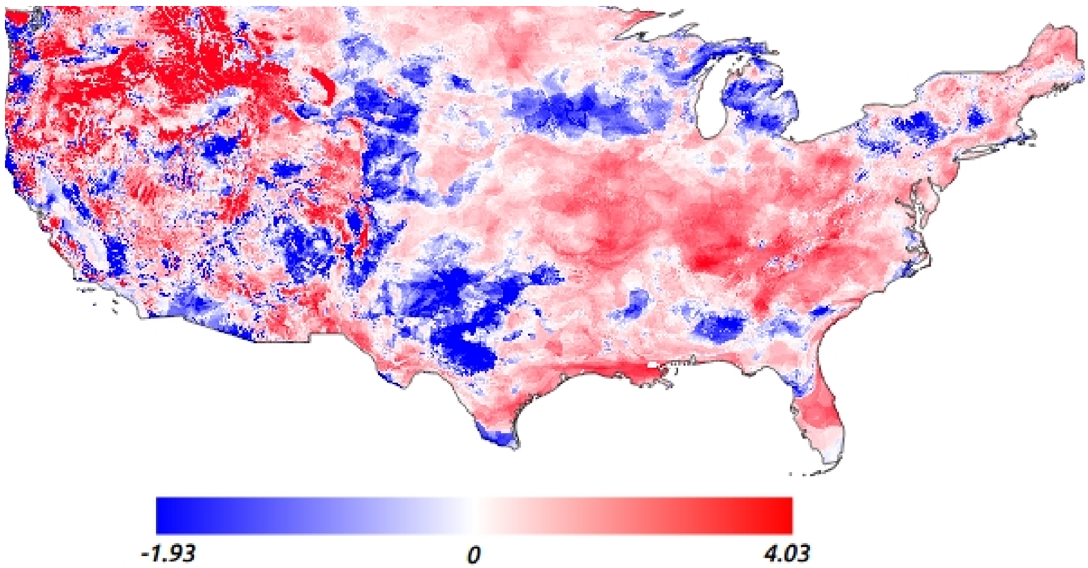

Figure 2: The trend of damage index from 1980 to 2015.

Figure 3 shows the probability of false spring which is the average of binary false spring grids for the period 1980 to 2015. The probability of false spring in the conterminous US was less than 0.5. As expected, the Midwest (especially upper Midwest and the Great Lakes) and Northeast have a higher probability of false spring than other parts of the US, while North Florida, which is not known as an icy area, has the smallest probability. This results are in line with the general findings of the literature, including Ault et al (2013)

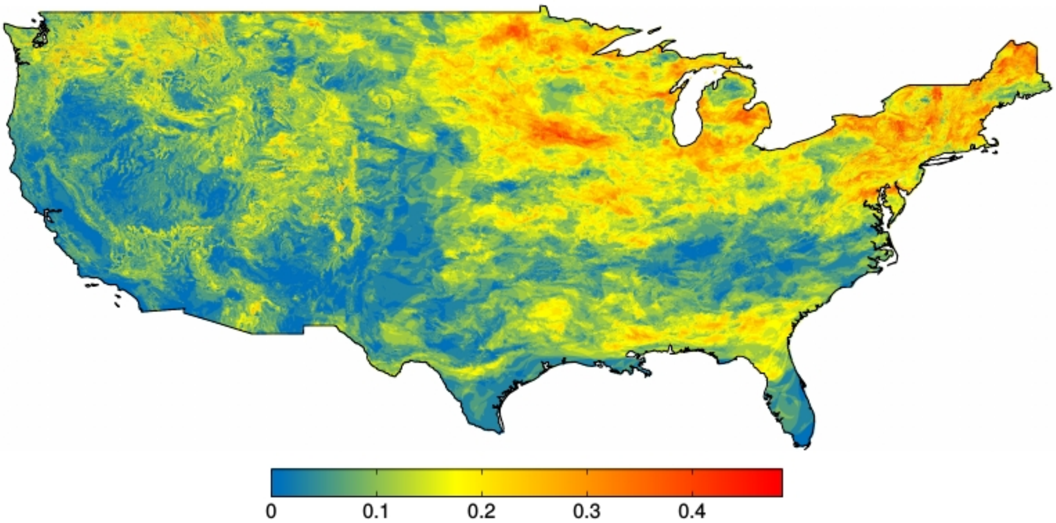

Figure 3: The average false spring from 1980 to 2015.

4. Conclusions

The developed cloud-based approach to map false spring at very high spatial resolution (1km), over larger areas (continental US) and for a long period (more than three decades) was computationally efficient. This allowed us to map the spatial pattern of false spring and to study its temporal trends. This information improves our understanding of the impact of climate change over terrestrial ecosystems. Our results revealed that the risk of false spring exists throughout much of the US while the risk is higher in the Midwest and Northeast than the rest of the US. This extensive regional variation highlights the need for future species-specific predictions to better understand potential effects on natural and agricultural systems.

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