Exploring the Influence of Source and Scale of Phenological Model Inputs at Continental Scale

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Abstract

Gridded time series of climatic variables are key inputs to phenological models because they allow the generation of spatially continuous products. To date, there have been few efforts to evaluate how the source and spatial resolution (i.e., scale) of the input data might affect how phenological models and associated indices track variations and shifts at continental scale. This study represents the first such assessment, based on cloud computing. We compared and validated gridded estimate of day of year (DOY) for First Leaf (FL) and First Bloom (FB) emergences in plants that were obtained using Daymet (at 1-km, 4-km, 35-km, and 100-km spatial resolution) and gridMET (at 4-km, 35-km, and 100-km) temperature data. These products were used to estimate temporal trends in DOY for first leaf and first bloom indices in the coterminous US (CONUS) from 1980 to 2016. DOYs driven from gridMET are substantially biased toward later DoYs by up to four months.

Keywords: Climate change, spatial-temporal trend analysis, spring phenology, volunteered geographic information (VGI), cloud computing, gridded time series analysis

1. Introduction

Climate variability and change affect the timing of plant development, most conspicuously after winter dormancy breaks in early spring (Cayan et al., 2001; Schwartz et al., 2006; Schwartz et al., 2013; Post et al., 2018). Such shifts have significant ecological, hydrological, and economic consequences. Phenology is the science that deals with the study of annual life cycle events (phenophases) in plants and animals, and how variation in environmental conditions affect the timing of these events (Lieth, 1974). Plant spring phenology is commonly expressed in terms of day of year (DOY) for key phenophases, following established observation protocols such as First Leaf (FL) and First Bloom (FB) emergences (Schwartz, 1998; Wolfe et al., 2005). A suite of statistical models referred to as Extended Spring Indices (SI-x) successfully generalize the DOY at regional to continental scales (Schwartz et al., 2006; Schwartz et al., 2013; Ault et al., 2015). SI-x indices are widely used in the Northern Hemisphere to estimate patterns and trends in spring onset (Wu et al., 2016; Belmecheri et al., 2017; Zhu et al., 2017).

The recent improvement in interpolation algorithms and computational technologies have led to gridded daily weather datasets such as Daymet (Thornton et al., 1997), available at 1-km resolution and gridMET (Daly et al., 2007), available at ~4-km (1/24th degree) resolution. These two products are generally the most frequently used datasets overall, and they are the most accurate gridded products available to calculate SI-x in the US. The impact of Daymet and gridMET on SI-x indices have not been evaluated. This is because such evaluation requires extensively distributed reference phenological observations and adequate computational power. Enhancements in large-scale distributed computing paradigm such as cloud computing facilitate processing of higher spatial resolution, gridded data (Guo et al., 2010).

This study analyses the effects of Daymet and gridMET data and their spatial resolution on gridded SI-x products in the conterminous US. SI-x indices using Daymet at and gridMET are used to estimate and compare longer-term-average SI-x products using different spatial resolutions. These products also were validated using VPOs. In addition, temporal trend in SI-x indices using Daymet and gridMET was estimated and compared at four different resolutions.

2. Materials and methods

The data used in this study consist of gridded daily temperatures to generate the SI-x indices at 1, 4, 35 and 100-km, and VPOs to validate generated SI-x indices. Temperature data are daily maximum and minimum temperature extracted from Daymet and gridMET. Volunteered phenological observations (VPOs) were used as reference observations to assess the accuracy of the different SI-x products. The most long-term and continentally-extensive VPO's available for CONUS are for phenophases of lilacs (*Syringa vulgaris* 'common lilac' and *S.* x *chinensis* 'Red Rothomagensis) and honeysuckles (*Lonicera tatarica* 'Arnold Red' and *L. korolkowii* 'Zabelli') from 1955 to 2016 (Rosemartin et al., 2015). The data consist of the DOY that FL and FB happened each year for lilac and honeysuckle at observed locations. The SI-x estimates the DOY of FL and FB obtained by the time average of the FL and FB of three models from leafing and flowering of the four lilac and honeysuckle species.

The sensitivity of the SI-x indices respect to the spatial resolution and input data was analysed using Google Earth Engine (GEE) cloud computing platform, in the following steps. In the first step, daily maximum and minimum temperature and day-length from Daymet were spatially aggregated from 1-km to 4, 35 and 100-km. Similarly, gridMET datasets were spatially aggregated from 4-km to 35 and 100-km. For each year, in the second step, gridded SI-x indices were generated from 1-km, 4-km, 35-km, and 100-km Daymet and 4-km, 35-km, and 100-km gridMET (Izquierdo-Verdiguier et al., 2018). Moreover, the long-term average of SI-x was calculated for indices driven for all spatial resolution cases. The long-term difference between the SI-x products was calculated to help explore and compare regional variations in the difference between gridded SI-x products. The differences are the pairwise subtraction of pixels values of 4-km, 35-km. and 100-km Daymet and gridMET. In the last step, the temporal trend in the SI-x products were calculated and compared. For each pixel, the trend was obtained by fitting a linear regression line to annual SI-x indices, from 1980 to 2016. The slope of the line is the rate of change of SI-x indices per year.

3. Results and discussion

For long-term SI-x indices, the SI-x products generated from 1-km, 4-km, 35-km and 100-km Daymet (SI-x Daymet) are substantially different from SI-x products generated from 4-km, 35-km and 100-km gridMET (SI-x gridMET). However, visual exploration of SI-x Daymet in 1-km, 4-km, 35-km and 100-km and SI-x gridMET at 4-km, 35-km and 100-km resolutions shows that change in spatial resolution of SI-x input has no influence on spatial pattern of SI-x outputs (Figure 1). The long-term SI-x gridMET show later FL and FB compare to SI-x Daymet. The long-term differences between SI-x Daymet and SI-x gridMET are substantial for 4, 35 and 100-km (Figure 2 where the differences were plotted in steps of one week). These results indicate that SI-x indices are sensitive to input data that affect the estimated DOY of FB more than FL.

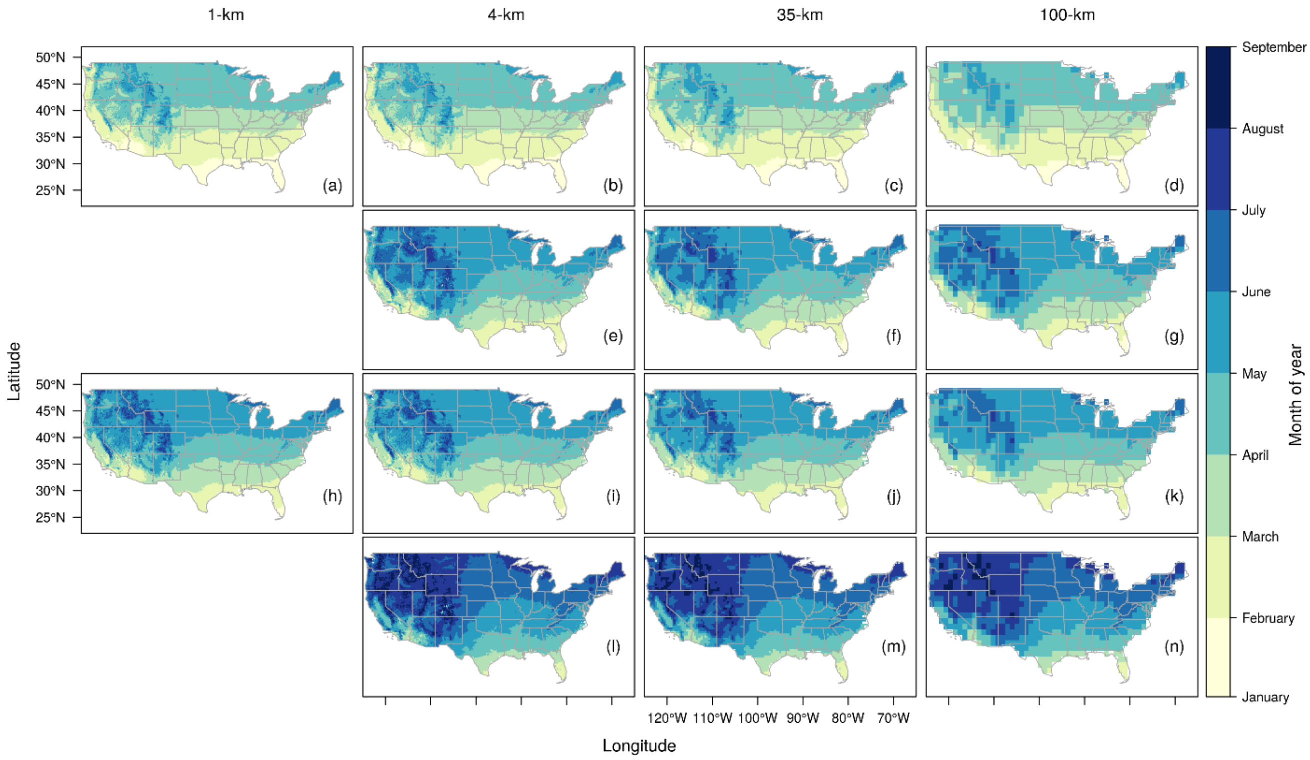

Figure 1. Long-term SI-x FL from (the first row: a, b, c and d) Daymet and (the second row e, f and g) gridMET, and Long-term SI-x FB from (the third row: h, i, j and k) Daymet and (the forth row: l, m and n) gridMET, from1980 to 2016.

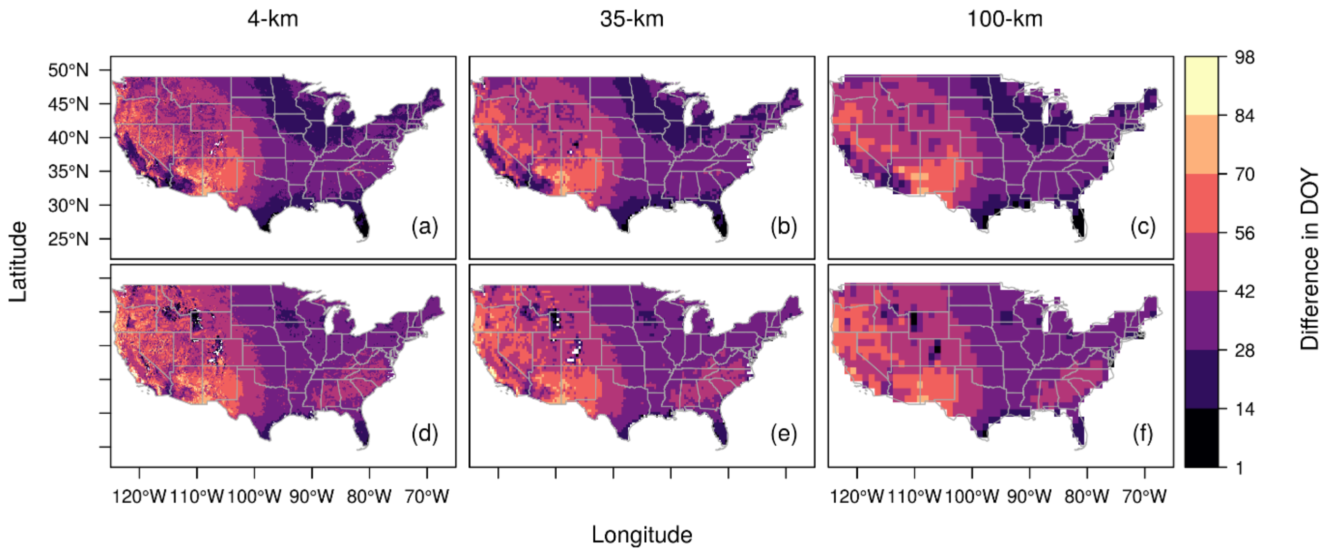

Figure 2. Maps of the difference between (the first row: a, b and c) SI-x FL products and (the second row: d, e and f) SI-x FB products.

The regression line fitted to annual SI-x indices, from 1980 to 2016, helps explore temporal variations in SI-x Daymet and SI-x gridMET across the US. The slope of regression lines was mapped by generalizing in 0.2 steps, which indicate about one week change per the study period (Figure 3). For both Daymet and gridMET, the maps of temporal trend in SI-x products show the similar spatial pattern in selected spatial resolutions. This is because these products exhibit no substantial differences. Both SI-x Daymet and SI-x gridMET show advancement in DOY of FL and FB for most of the locations in the US, ranging from one to five weeks from 1980 to 2016. However, the advancement in FB (Figure3: the second and fourth rows) covers larger areas than the advancement in FL (Figure3: the first and third rows).

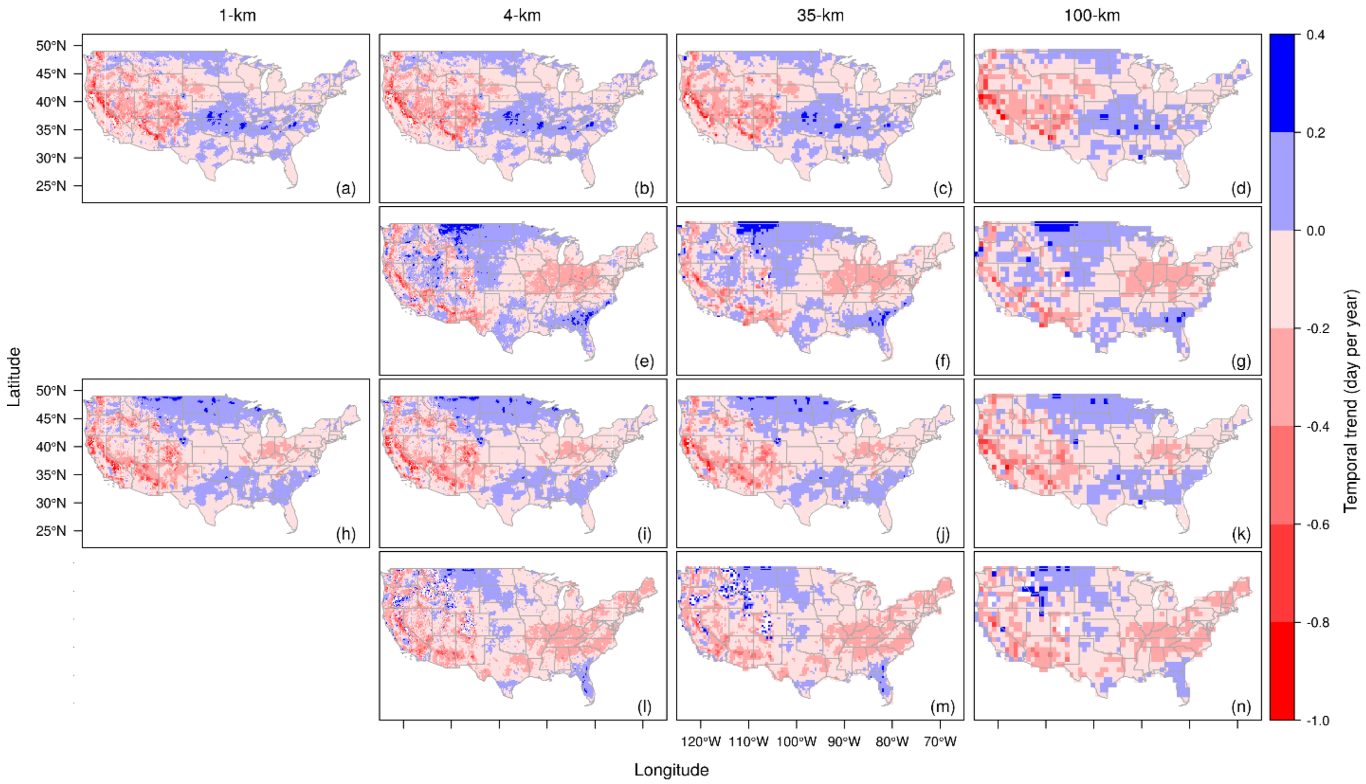

Figure 3. Trend maps of SI-x FL from (the first row: a, b, c, d) Daymet and (the second row: e, f, g) gridMET, and trend maps SI-x FB from (the third row: h, I, j and k) Daymet and (the fourth row: l, m and n) gridMET.

4. Conclusions

The evaluation of the effect of gridded time series input on the Extended Spring Indices (SI-x) is necessary because these indices are being increasingly used as national and official indicators of climate change in the US. This paper presents an exploratory workflow for analysing the effect of input data and spatial resolution of the SI-x indices at a continental scale. We used cloud computing and volunteered phenological observations to generate, compare and validate SI-x using Daymet and gridMET at selected spatial resolutions. We also analysed the impact of spatial resolution and input data on estimation of temporal trends.

Our results show that changing the spatial resolution does not substantially affect the long-term SI-x indices or the temporal trend in these products. However, the change in input data affects SI-x indices and, hence, the temporal trends in spring onset. The SI-x indices generated from gridMET are substantially biased toward later days of year, by up to four months. Our results also indicate that the SI-x indices generated from both datasets exhibit the highest variation in FL and FB in the western US, as it might be expected for mountainous areas. Yet both Daymet and gridMET -based indices show advances in FL and FB indices over most of the U.S.

The proposed workflow can be applied to explore the effect of other high-resolution gridded time-series inputs on phenological models. By evaluating the translation of gridded input data into information, this workflow can also support other environmental and ecological studies being used to investigate the impact of climate change at local scales.

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