Responses to Anonymous Referee #2

Summary:

Xu et al. manuscript presents a comparison of spring greenup (SG) and its sensitivity to temperature and precipitation over the northern hemisphere inferred from two remote sensing NDVI products (MODIS and GIMMS) over the period 2001-2013. They aim at exploring the uncertainties in NDVI SG trends and sensitivity to climate. They conclude that both products are consistent in mid latitudes both for SG and its sensitivity to climate, but show different magnitude and trends in high latitudes.

General Comments:

The analysis performed in this study is timely, but the main message and the novelty of the study remain unclear.

First, the authors did not really assess the uncertainties induced by NDVI products and the approach used. Previous studies already highlighted differences in SG and its temporal trend estimated by several approaches and different NDVI products (Chang et al. 2016, Wang et al. 2015, Ding et al. 2015 for example). It is already known that main uncertainties in estimating SG are found in high latitudes. Xu et al. went one step further by comparing SG sensitivity to climate between products but mainly concluded about observed differences, not the uncertainty behind, which in the end led to the same conclusion than previous studies. Because differences in SG estimates leads to differences in pre-season length, the authors compared sensitivities that are not really comparable. The uncertainty in sensitivity to climate results from the propagation of the uncertainty in SG estimates, however these aspects are poorly discussed in the manuscript.

Authors: We sincerely thank the reviewer for the constructive remark. In the revision, we have edited and rewritten parts of this manuscript. Further analyses are provided. Our responses and detailed edits are indicated below in the point-to-point responses.

Secondly, the methodology suffers from major flaws. Only one method is used to smooth and fit the data while previous studies highlighted a strong impact of the smoothing method (Atkinson et al. 2012) and approach used to estimate SG. Moreover we don't have information about the performance of the approach. The authors did not take into account partial correlations between temperature and precipitation, thus leading to weak interpretations of the results (Fu et al. 2014). Finally the filtering of data performed in the analysis is sometimes unjustified or incomplete (see specific comments). The authors should refine their research question to be in adequation with their approach or go deeper in the analysis of uncertainty propagation from NDVI products to the estimation of climate sensitivity of SG.

Authors: We add a paragraph in section 2.4 to elucidate why we use a single method to smooth NDVI time series and derive greenup-date other than multi-methods. The common used regression methods to reconstruct NDVI time series and derive SG include Savitzky-Golay fitting method, spline smoothing, asymmetric Gaussian functions, double logistic function, and harmonic analysis of times series. These methods are valid in fitting NDVI gaps and reducing noise (Cai et al. 2017), however, they can make differences in estimating phonological stages (Cong et al., 2013). It is hard to justify which method is better (Atkinson et al, 2012). In order to reduce the mixed uncertainty of reconstruction methods and NDVI products, here we used one regression method to reconstruct the NDVI series. The double logistic method uses least-square fitting to half growing season (Zhang et al., 2003). It is more robust than other methods in estimating the vegetation seasonal dynamics, when there is no local calibration (Cai et al., 2013). Atkinson et al. (2012) also proved that the double logistic method is reliable to smooth the noise, when it is applied to a single growth cycle. Following reviewer's suggestion, we further specified our research objectives in Introduction. We refined our analysis and made more comparison between other recent studies with different products and methods and our results. The uncertainty due to sensors resolution and algorithm are provided in discussions.

Atkinson, P. M., C. Jeganathan, J. Dash, C. Atzberger (2012). Inter-comparison of four models to smoothing satellite sensor time-series data to estimate vegetation phenology. Remote Sensing of Environment, 123, 400-417.

Cai, Z., P. Jönsson, H. Jin, L. Eklundh (2017). Performance of smoothing method for reconstructing NDVItime-series and estimating vegetation phenology from MODIS data. Remote Sensing, 9, 1271, doi:10.3390/rs9121271.

Cong, N., T. Wang, H. Nan, Y. Ma, X. Wang, R. B. Myneni, S. Piao (2013). Changes in satellite-derived spring vegetation green-up date and its linkage to climate in China from 1982 to 2010: a multi-method analysis. Global Change Biology, 19, 881-891, doi:10.1111/gcb.12077.

Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A. (2003). Monitoring vegetation phenology using MODIS. Remote Sensing of Environment, 84, 471–475.

Specific Comments:

L.96: the paper from cong et al. is not an evidence that methods in estimating SG has no impact on resulting trends and sensitivity. Especially for sensitivity to climate that requires the estimation of the pre-season length, there will be a propagation of errors that will influence final results.

Authors: Thanks for this insightful suggestion. We rephrased this sentence and in response to reviewer's general comment above, we add a paragraph in section 2.4 to provide more information about the methods to smooth NDVI time series and derive greenup-date. Cong et al. (2013) proposed that the different methods can lead to varied magnitude of SG shift, however, the signs of SG trend are consistent across regions and vegetation types over the same period, when the methods are applied to the same NDVI products. We use the same method and aim to prove that the conflicted SG shift is caused by the different NDVI products and the different NDVI based SG shift propagate the uncertainties in determining the SG sensitivity to climate changes.

L.135: now CRU-NCEP v.8 is extended to 2017. Remove "recently extended"

Authors: We rephrased this sentence.

L.145: maybe use the median value.

Authors: It would be interesting to evaluate the difference between the mean value and median value when resampling the NDVI products from a high resolution to a low resolution. The commonly used resampling methods include averaging, bicubic, bilinear interpolation and nearest neighbor. Here we keep the spatial averaging method that has been widely applied to NDVI resampling by other studies, e.g. Zeng et al. (2013), Fensholt et al. (2006) and Busetto et al. 2008.

Zeng, F.-W. , Collatz, J. G., Pinzo, J. E., Ivanoff, A. (2013) Evaluating and quantifying the climate-driven interannual variability in Global Inventory Modeling

and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI3g) at global scales, Remote Sensing, 5, 3918-3950.

Fensholt, R., T.T.Nielsen, S. Stisen (2006) Evaluation of AVHRR PAL and GIMMS 10-day composite NDVI time series products using SPOT-4 vegetation data for the African continent, International Journal of Remote Sensing, 2006, 2719-2733.

Busetto, L.,M. Michele,R.Colombo(2008)Combining medium and coarse spatial resolution satellite data to improve the estimation of sub-pixel NDVI time series, Remote Sensing of Environment, 112, 118-131.

L.142 & 179: Is 15days observation fine enough to estimate sensitivity to climate change properly? Moreover, is it significant to estimate the pre-season length with a 3days step when observations are performed every 15 days?

Authors: NDVI time series at 15-day scale is too coarse to indicate the phonological stages. So that, we fit the NDVI time series to a finer scale to obtain the vegetation growth trend and seasonality. Here, we fitted NDVI to daily scale to match the climate data. The double logistic method allows for fitting and smoothing GIMMS NDVI at 15-day (Sobrino and Julien, 2011) or MODIS NDVI at 16-day scale (Hird and McDermid, 2009). As NDVI is fitted and smoothed to a daily scale, it is finer enough to match the pre-season with 3-day step.

Hird, J. N., G. J. McDermid (2009). Noise reduction of NDVI time series: An empirical comparison of selected techniques. Remote Sensing of Environment, 113, 248-258.

Sobrino, J. A. and Y. Julien (2011). Global trends in NDVI-derived parameters obtained from GIMMS data. International Journal of Remote Sensing, 32, 4267-4279.

L.179-183: explain why?

Authors: The temporal and spatial distribution of precipitation is heterogeneous. Therefore, we use the relative variation in precipitation to take the variation and baseline precipitation in each pixel.

L.184: the authors should use partial correlations to take into account co-variations of climate.

Authors: Following the reviewer's suggestion, we further analyzed the partial correlation between SG and preseason temperature (Figure R2) and precipitation (Figure R3). We found that the pattern of the partial correlation is close to our calculated Pearson Correlation for both temperature and precipitation. Using the partial correlation, we can reach the same conclusion that temperature overwhelms precipitation as the major driver of the spring phenology.

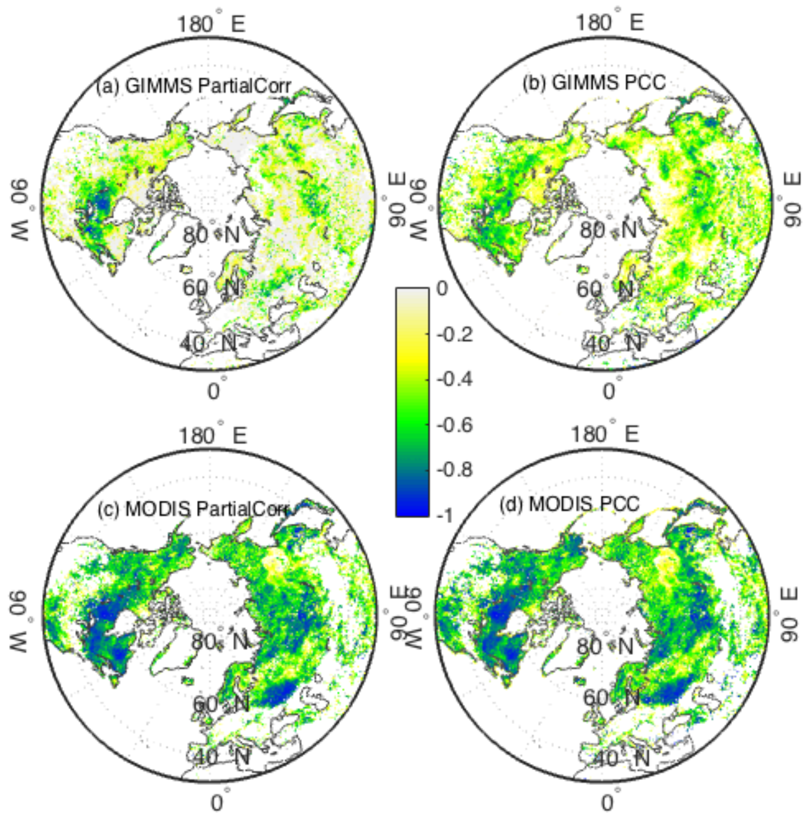

Figure R2 Partial correlation (left panel) and Pearson correlation (right panel) between SG and preseason temperature for GIMMS (a, b) and MODIS (c, d).

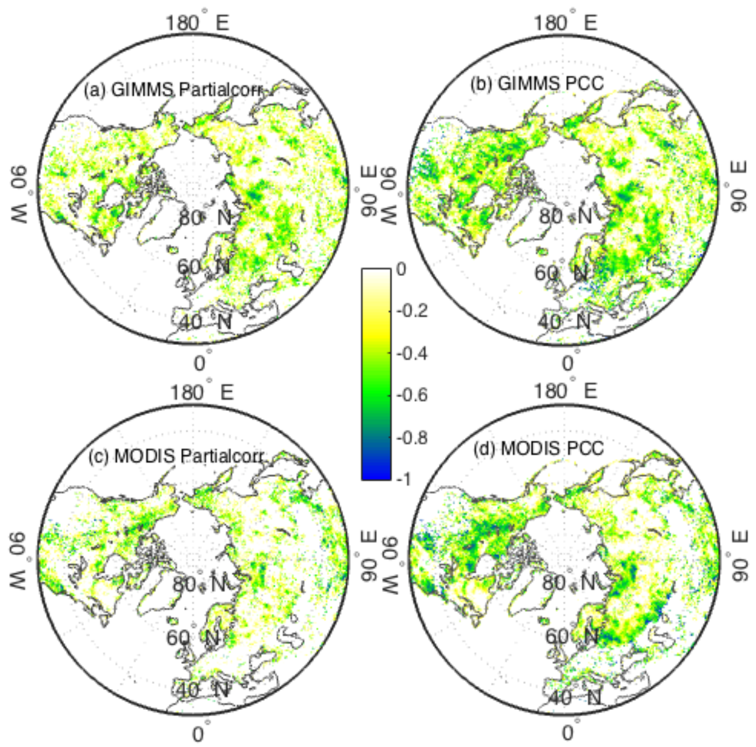

Figure R3 Partial correlation (left panel) and Pearson correlation (right panel) between SG and preseason precipitation for GIMMS (a, b) and MODIS (c, d).

L.187 & 195: why removing positive correlations? Several studies highlighted different

behaviours according to species and regions (Zhang et al. 2016 for example). By removing positive correlations you start the analysis by assuming that vegetation respond all the time negatively to climate change which is not true. If the aim is to compare both products the authors should keep all the information available.

Authors: In our revision, we supplemented the pixels with insignificant response to temperature and precipitation (Figure 4). As we focused on the green-up and climate control in spring, it is reasonable excluded the positive interannual correlation between preseason climate and green-up date shift. In Zhang et al. (2016), the observations indicated the spring temperature warming induced the advancement of leaf unfolding in 99.7% of the studied cases, either significant (48.8%) or insignificant (50.9%). Only 0.3% of the studied cases showed spring warming and delayed leaf unfolding relationships.

L.194: OLS or SMA regression. In this case SMA regression are more appropriate

Authors: The Ordinary Least Square (OLS) regression is appropriate for the relationship between two variables that are clarified with one independent variable and one dependent variable. The Standard Major Axis (SMA) regression is suitable for the cases in which the independent and dependent variables are not clear. In our study, the phonological change is a response to climate drivers, i.e. SG is the dependent variable and climate drivers are independent variables.

L.195: why not excluding non-vegetated pixels? It would improve the analysis.

Authors: we screened the pixels with maximum NDVI < 0.1 that potentially excluded the non-vegetated pixels.

L.195: to avoid a bias due to the number of significant pixels, the authors should compare only pixels for which significant sensitivities can be estimated for both products.

Authors: In our revision, we displayed the pixels with insignificant response to temperature and precipitation and marked the pixels with 90% confidence level with black dots (Figure 4). Our results are based on the pixels with significant sensitivity. But in response to reviewer #1, we add the mean sensitivity of SG to temperature and precipitation in section 3.3 for all the pixels. For the biome-scale sensitivity of SG to temperature, we found that filtering with ($p<0.1$) criteria tends to exclude pixels with lower sensitivity. But the stronger sensitivity inferred by MODS SG than that inferred by GIMMS SG remains with/without p-value filtering.

L243: check partial correlations between SG temperature and precipitation.

Authors: Please see our responses above for L.184.

L247: a significant correlation does not mean a control. Please reformulate

Authors: We accept reviewer's suggestion and rephrased.

L.252-256: how does it relate to changes in SG?

Authors: The Pearson Correlation Coefficient is calculated between time of SG and preseason temperature and precipitation (Section 2.4). The higher PCC indicates a better correlation between time SG and preseason climate.

L.271: Does +/- 7 or 4mm means a significant change in precipitation? .

Authors: In response to this reviewer comment, we provide a figure below to show the total preseason precipitation (mm) correlated to GIMMS derived SG. The distribution of preseason precipitation is very heterogeneous. But the maximum 7mm yr^{-1} and -4mm yr^{-1} in preseason means a strong change in most regions. Due to the strong heterogeneity, we use the relative change of precipitation to assess the sensitivity of spring phenology to precipitation change.

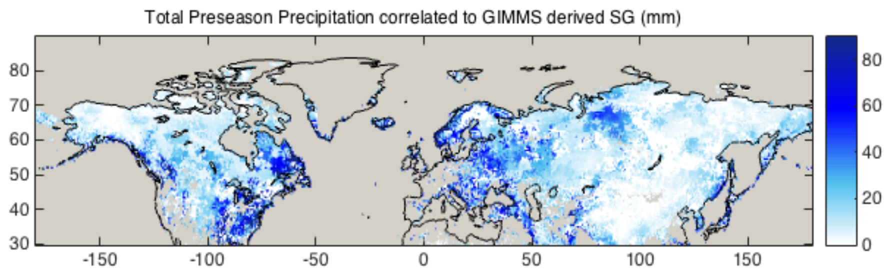

Figure R4 Total preseason precipitation correlated to GIMMS derived SG.

L.275: because we don’t have the same pre-season length it is difficult to conclude.

Authors: The preseason is determined as the period in which mean temperature (or precipitation) is best correlated with SG. The difference in preseason length indicated the uncertainties in SG-climate links propagated from uncertainties in SG predictions. If we use the same pre-season, e.g. spring season, the sensitivity of SG to climate would be calculated by regression of SG derived from different NDVI products with the same climate, from which there must be different sensitivities of SG to climate due to different SGs. But the SG-climate links would be concealed. In reality, the period during which the temperature controls the interannual variability and long term trend of spring phenology is debated depending on different methods and varied across regions and biomes. The Europe-wide earlier growing season was analyzed in correlation with the warming spring during February-April (Chmielewski and Rotzer, 2001) while variation in spring phenology of temperate tree species in south-west France was attributed to the temperature variation during March-May (Vitasse et al., 2009). The correlation analysis between the spring phenology and temperature in different period imply that temperatures in different time-scales have been reported to play different roles across regions and biomes. In horticultural woody perennials in northeastern USA, the warming trend in annual temperature is well correlated to the spring advance, while the warming trend in monthly March and April temperature was not very significant (Wolfe et al., 2005). The phenology changes in some Mediterranean species were most correlated to the temperature changes in the months preceding the phenological events while other species correlated to the annual temperature changes (Peñuelas et al., 2002). In 254 records from nine European coutries, 19% of the phenophases are highest correlated with the temperature in the month of onset, 63% with preceding month and 18% with 2 months earlier (Menzel et al., 2006).

Chmielewski, F. M., and T. Rotzer, 2001: Response of tree phenology to climate change across Europe. Agricultural and Forest Meteorology, 108, 101–112.

Vitasse, Y., A. J. Porté, A. Kremer, R. Michalet, S. Delzon (2009) Response of canopy duration to temperature changes in four temperate tree species: relative contributions of spring and autumn leaf phenology, Oecologia, 161, 187-198.

Wolfe, D. W., M. D. Schwartz, A. N. Lakso, Y. Otsuki, R. M. Pool, N. J. Shaulis (2005) Climate change and shifts in spring phenology of three horticultural woody perennials in northeastern USA, International Journal of Biometeorology, 49, 303-309.

Peñuelas, J., I. Filella, P. E. Comas (2002), Changed plant and animal life cycles from 1952 to 2000 in the Mediterranean region, Global Change Biology, 8, 531-544.

Menzel, A., T.H. Aparks, N. Estrella, E. Koch, A. Aasa et al. (2006) Erupoean pheanological response to climate change matches the warming pattern, Global Change Biology, 12, 1969-1976.

L.280: why it is not responsive to precipitation?

Authors: Temperature has long been recognized as the dominant factor that alters SG. For example, the records of tree SG over 100 years from England (Thompson & Clark, 2008) and flowering in the northeastern U.S. (Miller-Rushing & Primack, 2008) have chronicled advances of 3–8 days for each 1°C increase in air temperature over the 1 or 2 months preceding the SG or flowering. European larch in northern Italy Alpine regions has advanced at a rate of 7 days per °C increase in spring air temperature (Busetto et al., 2010). The vegetation types with earlier mean SG in lower latitude are more sensitive to temperature increases and show larger advances over the historical period (Shen et al., 2014), and 88% of the latitudinal variability in the SG trend can be explained by preseason temperature (Shen et al., 2015). Even in the regions with permanent or periodic water stress, water availability is recognized as a secondary factor that mediates the phonological cycle (Seghieri et al., 2012).

Thompson, R., & Clark, R. M. (2008). Is spring starting earlier? Holocene, 18, 95–104. https://doi.org/10.1177/0959683607085599

Miller-Rushing, A. J., & Primack, R. B. (2008). Global warming and flowering times in Thoreau's concord: a community perspective. Ecology, 89, 332–341. https://doi.org/10.1890/07-0068.1

Busetto, L., Colombo, R., Migliavacca, M., Cremonese, E., Meroni, M., Galvagno, M., Pari, E. (2010). Remote sensing of larch phonological cycle and analysis of relationships with climate in the Alpine region. Global Change Biology, 16, 2504–2517. https://doi.org/10.1111/j.1365-2486.2010.02189.x

Shen, M., Tang, Y., Chen, J., Yang, X., Wang, C., Cui, X., … Cong, N. (2014). Earlier-Season Vegetation Has Greater Temperature Sensitivity of Spring Phenology in Northern Hemisphere. PLoS ONE, 9(2), e88178. https://doi.org/10.1371/journal.pone.0088178

Seghieri, J., Carreau, J., Boulain, N., De Rosnay, P., Arjounin, M., & Timouk, F. (2012). Is water availability really the main environmental factor controlling the phenology of woody vegetation in the central Sahel? Plant Ecology, 213, 861–870.

Shen, M., Cong, N., & Cao, R. (2015). Temperature sensitivity as an explanation of the latitudinal pattern of green-up date trend in northern Hemisphere vegetation during 1982–2008. International Journal of Climatology, 35, 3707–3712. https://doi.org/10.1002/joc.4227

L.283: percent compared to which value?

Authors: We rephrased this sentence.

L.300: interesting result. It is consistent with field observations over Europe (Fu et al. 2015)

Authors: Thanks. This is an interesting study and we cited it.

L.312: recent studies showed that CCI is better than NDVI in detecting phonological changes for evergreen (Gamon et al. 2016). That may explain the behaviour of evergreen vegetation in this study.

Authors: Thank you for suggesting this publication. We add Gamon et al. 2016 in our discussion.

Technical comments:

Figures 2abc are not cited in the text

Authors: Figure 2a, b and c are now cited in section 3.1.

As you compare both products figure s1 is more relevant than figure 1. Try to use absolute or relative comparisons in the main figures and put absolute values in supp, also for fig3. Moreover the scale make it difficult to see where differences are null.

Authors: We changed the Figure 1 and Figure 3 as suggested.

Atkinson, Peter M., et al. "Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology." Remote sensing of environment
123 (2012): 400-417.

Wang C, Cao R, Chen J, Rao Y, Tang Y. 2015. Temperature sensitivity of spring vegetation phenology correlates to within-spring warming speed over the Northern Hemisphere. Ecol Indic. 50:62–68.

Ding M, Li L, Zhang Y, Sun X, Liu L, Gao J,Wang Z, Li Y. 2015. Start of vegetation growing season on the Tibetan Plateau inferred from multiple methods based on GIMMS and SPOT NDVI data. J Geog Sci. 25:131–148. Better consistency with observations is the threshold

Chang, Qing & Zhang, Jiahua & Wenzhe, Jiao & Yao, Fengmei. (2016). A comparative analysis of the NDVIg and NDVI3g in monitoring vegetation phenology changes in the Northern Hemisphere. Geocarto International. 33. 1-20. 10.1080/10106049.2016.1222633.

Zhang, H.,W. Yuan, S. Liu, andW. Dong. 2015. Divergent responses of leaf phenology to changing temperature among plant species and geographical regions. Ecosphere
6(12): 250. http://dx.doi.org/10.1890/ES15-00223.1

Gamon, John A., et al. "A remotely sensed pigment index reveals photosynthetic phenology in evergreen conifers." Proceedings of the National Academy of Sciences 113.46 (2016): 13087-13092.