Dear Dr. Keenan, 1 2 We greatly appreciate your precious time in handling our manuscript. We have carefully 3 addressed each of two anonymous reviewer's comments and also revised the whole manuscript 4 for readability. Our point-by-point response to each of reviewer's comments was listed below 5 and marked in blue color. In addition, the revised manuscript with track-changes was attached 6 following our responses to two anonymous reviewer's comments. 7 8 Again, we appreciate your help in helping improving our manuscript. For any further 9 requirement, please feel free to let us know. 10 11 12 Sincerely yours, 13 14 **Guoping Tang** 15 On behalf of all coauthors 16 **Desert Research Institute** 17 18 19 20 **Responses to two anonymous reviewer's comments:** 21 Anonymous Referee #1 22 Received and published: 21 September 2015 23 24 25 General comments The Tang et al. paper presents a study investigating the trends and interannual variability (IAV) 26 in vegetation greenness and associated drivers the semi-arid/arid ecosystems in the US Great 27 Basin over the 1982-2011 period. The two main findings of the paper are that the warming trend 28 is the main driver of the increased Growing Season Length (GSL) due to a later autumn 29 senescence but that precipitation drives the IAV in greenness. 30 31 The study is a valuable contribution to the literature as there is a relative lack of publications 32 investigating trends for semiarid ecosystems compared to temperate/high latitude regions, as the 33 authors point out. The aims of this study are nicely written and there is a detailed analysis of the 34 possible drivers of the changes. There is a lot of detail in there that could potentially benefit 35 further clarification in the text – I will attempt to summarize these points below. 36 37 One issue that needs to be addressed is the difference between drivers of change in IAV and 38 trends. There is a mix of the impact of overall trend and IAV in the linear regression that needs 39 to be explained more clearly. The linear regression/correlation analysis (in Section 3.4 and 40 Figures 6-8) is based on the anomalies (the delta in these figures is the inter-annual anomaly 41 from my understanding, as the figure caption does not give enough detail). This delta (the 42

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anomalies) will include the changes due to both the IAV and the trend. The results however are

only discussed in terms of the drivers on IAV.

 Response: Thanks for your good comments. According to your suggestion, we conducted additional correlation analysis based on trends of a climatic variable and trends of a vegetation phonological index to examine the climatic drivers that may be responsible for the long-term trends of vegetation phenology during 1982-2011. We added new results to the section 3.4 for

5 *clarity*.

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Then in Section 4.1 all the results (both the description of long-term trends and the drivers of the 7 anomalies) are brought together to explain the long-term trends in a slightly confusing way, 8 which is not helped by the fact that new (and crucial) results are introduced (Figure 8 and Table 9 3) – so as a side point I think these results should be described in detail in the results section. For 10 example Figure 8a shows a positive relationship between the temperature and GSL anomalies, 11 12 but this could be the same even without any trend in either variable (i.e. in years with warmer temperatures, you would get a longer GSL). Then the authors refer to Figure 2, which shows the 13 14 long term trend, to suggest (together with Figure 8a) that the increase in long term temperature causes the increase in GSL (and NDVI). Although the logic mostly follows I am not sure that all 15 16 the pieces are there to make this picture.

Response: Again, based on additional analyses on the driver responsible for the trends of
 vegetation phenology, we revised the section 4.1 for clarity.

I think it would be clearer if the analysis in 3.4 wasn't just presented as a change in interannual variability but as anomalies that will include the underlying IAV and trend. I think a trend analysis could include a regression the trend (slope) in NDVI against the trend in temperature for each grid point (and see if there's a correlation). It would be interesting to assess just the drivers of IAV by de-trending the curve before performing the linear regression analysis. I am also unclear whether the multivariate regression compares the anomalies or the long-term trend.

Response: Thanks very much for your constructive comments. We conducted additional trend analysis by regressing NDVI against temperature or precipitation for the study region. We have added new results including new figures in the revised manuscript. The multivariate regression analyses were based on anomalies. The purpose of developing multivariate regression models was to examine what combination and interaction of climate variables may better explain the interannual variation of vegetation phenology. As you mentioned, because anomalies also included trends, we revised related text for clarity.

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I suggest that a bit more analysis to bring everything together, as well as a slightly clearer description of what's being analysed, would strengthen this paper. In addition I have a few remarks below about data processing that if addressed would further reinforce the conclusions drawn.

41 Response: We conducted additional analyses in the revised manuscript as you suggested. For 42 example, we revised the last paragraph of the introduction section for clarity. We clearly stated 43 that "the objectives of this study were to utilize the dryland ecosystems at lower elevation zones 44 of the U.S. Great Basin (Fig. 1) to (i) quantify long-term trends in mean vegetation greenness 45 (represented by Normalized Difference Vegetation Index (NDVI)), SOS, EOS, and GSL in the 46 of the U.S. Great Basin (Fig. 1) to (i) the distribution of the U.S. (NDVI), SOS, EOS, and GSL in the 46 of the U.S. (NDVI), SOS, EOS, and GSL in the 47 of the U.S. (NDVI), SOS, EOS, and GSL in the 48 of the U.S. (NDVI), SOS, EOS, and (SSL in the 49 of the U.S. (NDVI), SOS, EOS, and (SSL in the 40 of the U.S. (NDVI), SOS, EOS, and (SSL in the 40 of the U.S. (NDVI), SOS, EOS, and (SSL in the 41 of the U.S. (State State Sta

46 *dryland ecosystems that may have occurred during the most recent 30 years of climate warming;*

1 (ii) explore the spatial variation of long-term trends in vegetation greenness; (iii) and examine

2 the climatic sensitivity of trends and variability of vegetation phenology in the study region."

New results based on additional trend analyses were added to section 3.4 and discussed in the discussion section in the revised manuscript.

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6 Methods: Some technical data processing issues should be discussed further in the methods 7 section (again, details below) in order to strengthen the analysis. It is unclear in Section 2.4 8 whether the regression will be performed on the trend (per grid cell for example) or the 9 anomalies (per year). This should be clarified. I am unclear why a univariate and then a 10 multivariate regression are performed, I would have thought that only a multivariate regression 11 would be needed. It would be good to have the equations here, as well as for the AIC metric.

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13 *Response: We revised the whole sub-section of 2.4 for clarity (see the new section 2.4 in the*

14 revised manuscript). The purpose of conducting univariate linear regression analysis is to

15 examine if temperature or precipitation by itself can explain the interannual variability of

16 vegetation phenology during 1982–2011. The multivariate regression models based on

17 *temperature, precipitation and their interaction were developed to analyze the contribution of*

18 variation in temperature, precipitation and their interaction to variations in vegetation

19 phenology during 1982–2011. We mentioned these in the revised section. The reason that we did

not list those multivariate regression models was because they were determined through stepwise regression analysis (i.e., they were not determined in advance. The model with smallest

overall p-value was selected as the best multivariate regression model in the process of step-wise

23 *regression*).

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I was slightly surprised by the fact that GIMMS NDVI is used and not the latest version (3g).
This is freely available as far as I am aware and uses an updated algorithm that accounts for
some of the issues of the earlier version. It would be good to compare your analysis for both
versions.

Response: Sorry for our carelessness. The NDVI data we used are in fact GIMMS NDVI3g,
which can be deduced from the study period and also acknowledged in the acknowledgement
section in the original manuscript. We revised related text to make this explicit.

I also think that all trend analyses should ideally be verified by performing the same analysis with an independent dataset (e.g. MODIS). I know of one study that has says that trends derived for GIMMS in arid regions should be interpreted with caution (Fensholt and Proud, 2012, RSE, 119, 131-147), though I note they have used this dataset in another analysis that you cite. It would significantly strengthen your analysis if you repeated the analysis with an independent dataset.

42 Response: Thanks very much for your good comments. Actually, we used MODIS NDVI data at 43 the earlier stage of this study. For example, the solid redline in the following figure shows the 44 variation of MODIS NDVI in shrub- and grass-dominated lands in the study region during the 45 period of 2000 to 2010. In terms of NDVI trends (based on NDVI anomalies after subtracting 46 the long-term mean NDVI), we found that there is a relatively good agreement between MODIS

and GIMMIS NDVI. However, big difference in terms of the magnitudes of NDVI values may 1 exist between MODIS and GIMMIS NDVI data for the study region. Unfortunately, the external 2 drive that we used to store both MODIS and GIMMIS NDVI data at the early stage of this study 3 was dead and none of these original data were retrievable. When we repeated this study, we did 4 not include MODIS NDVI data for two reasons: First, the mismatch of time period between 5 MODIS and GIMMIS NDVI data (MODIS NDVI started only from February of 2000); Second, 6 although there are some discrepancies in the magnitudes of NDVI values between MODIS and 7 GIMMIS NDVI data, the two datasets are positively correlated with each other, suggesting that 8 9 the overall trends (2000 to 2010) of NDVI between the two datasets were similar. Therefore, 10 when we started to repeat this study, we only collected and processed the GIMMIS NDVI3g data because this dataset has a longer time period allowing us to use a longer climate data. In 11 addition, while the addition of MODIS NDVI data can help test the robustness of our research 12 findings it may raise new questions (as you mentioned) that require further study. In order to 13 14 address these questions, we would need to lengthen our manuscript and we feel that these 15 additional analyses would be beyond the scope this paper. Nevertheless, a comparison of 16 MODIS and GIMMS NDVI3g for the study region can indeed improve our understanding of vegetation phenological dynamics in the US Great Basin. 17





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Response: We agree with your comments. Generally, before interpolating bi-weekly NDVI data
 into daily values, we excluded those extremely abnormal NDVI values (e.g., negative NDVI

Finally, the methods used to interpolate between data points and to derive the SOS and EOS dates will be subject to some uncertainty. This is also true if there are multiple cycles, or many little "bumps" in the time series – how do you deal with this scenario?

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value). Because there were 4154 NDVI points considered in this study. It was hard for us to 1 check the little bumps in each of NDVI time-series for each of 4154 points. Although a few little 2 bumps may affect the determination of SOS and EOS at a given NDVI point, their effects on the 3

calculation of basin-wide SOS and EOS was minimized because of the numbers of points (4154) 4

used in this study. In addition, when using the cubic spline program to interpolate time-series 5

NDVI values at each grid point for a given day (e.g., march 7 of 2001) we used at least more 6

than ten continuous bi-weekly NDVI values. This approach ensured interpolated data fell within 7

8 the range (between the lowest and highest NDVI values) of all original NDVI values.

The IAV in particular of those dates might be strongly affected by this. An exhaustive 10 uncertainty analysis and quantification is probably too much to ask, but it would be good to do a 11 12 few tests to try and see how much different parameter or methods of interpolation affect your results, at least to mention this qualitatively in a few lines. 13

14 15 Response: Thanks for your good points! We added sentences such as "although we are confident 16 in our calculation of SOS and EOS, a validation of interpolation of time-series bi-weekly NDVI data to daily values may further enhance the accuracy of SOS and EOS estimates" in the 17 discussion section (see section 4.5 in the revised manuscript). As we mentioned before, because 18 the analysis of IAV was based on basin-wide average anomalies, we believe the impacts of NDVI 19 abnormal values were greatly minimized. 20

Results and discussion 22

23 More detailed figure captions are needed for those who might look at the plots first. For example for Figure 6 given the description in the results I assume each point corresponds to a year here 24 (therefore the anomalies from figure 2 etc) but if I just look at the plot I am not sure whether in 25 fact we are looking at the long term trend (change in temperature/NDVI) for each grid box. 26

Response: We revised the captions of most figures to improve their readability. 28 29

As stated above, the fact that the regression analysis will include the effects of both IAV and 30 trends should be discussed. 31

33 Response: According to your comments, we conducted additional trend analyses and added new results to the revised manuscript. 34

35 The discussion does nicely try to bring all the analysis together to form a clear picture, which is 36 difficult given all the metrics, time periods and difference between trends and IAV detailed in the 37 results. The main message is there but at times it's a bit confusing and needs to be described 38 more clearly, and the physical reasons could be discussed or emphasised. 39

Response: Thanks. We have tried to revise the discussion section to make it easier to follow. 41

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43 One main conclusion is that increased temperature SSA is responsible for the increased GSL, but 44 from what you show earlier that it appears to be the advancing EOS that is increasing the GSL,

45 but the summertime temperature that appears to be dominating the increase in SSA temperature.

At the same time the summer temperature has a negative relationship with summer NDVI (this 46

makes sense as if it's hotter the vegetation suffers from water stress). This means that you are 1 implying that increased summer temperature then has a positive effect on the length of the 2 growing season in the autumn, even if the plant has suffered water stress. This might be shown 3 further by considering pre-season temperature as well as precipitation in your correlation 4 analysis? You then show that summer and autumn NDVI is correlated with wintertime (and 5 autumn) precipitation and this explains why increased temperatures can explain the longer 6 growing season. I.e. the temperatures overall are increasing in the summer, and despite any water 7 stress that might decrease magnitude of the NDVI a positive precipitation anomaly helps the 8 9 overall trend in temperature. This is despite the lack of trend in precipitation, so this should be clearly explained. This summary of what's happening also perhaps explains the lack of 10 relationship between SSA temp and mean NDVI (i.e. you have a longer GSL but a decreased 11 12 summer magnitude contributes to no trend in SSA mean NDVI overall). I feel this kind of 13 discussion is nearly there but could be more complete. It might be good to examine the 14 amplitude in your analyses as well to complete the picture. Note also here that it might be worth 15 stating that by considering summer NDVI you are effectively (mostly I guess) looking at the 16 NDVI magnitude, whereas the SSA NDVI will include both magnitude and length.

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19 Response: Based on results from additional trend analyses, we found that the 30-year significant positive trends in both EOS and GSL were mainly attributed to the positive trend (although 20 statistically non-significant) of mean temperature in autumn. Although statistical analysis 21 suggested that mean temperature in summer was significantly correlated with the variation of 22 both GSL and NDVI in SSA, we suspect that these relationships were pseudo-relationships and 23 have no physical meaning given that temperature in summer was strongly negatively correlated 24 with summertime NDVI. We agree with your comments. Because NDVI in summer was 25 significantly and negatively correlated with summertime temperature while summertime 26 temperature had a significant increasing trend during the study period, this may partly have 27 caused SSA temperature to be uncorrelated with mean NDVI in SSA. We mentioned such a 28 mechanism in the discussion section of the revised manuscript. 29

I would like to see a discussion of whether the vegetation type influences the spatial patterns of the trends seen, and not just latitude (if you think there is a pattern – but I would be surpised if there was no effect). Although there was a strong negative trend in all seasons in the SW, this was not really discussed.

Response: Thanks for your good comments. At the first stage of this study, we have tried to 36 summarize vegetation phenological dynamics by vegetation types, i.e., Grass-dominated lands, 37 shrub-dominated lands and cheatgrass dominated lands (see Figure example below). We have 38 used to NLCD 2001 data and GLCF land cover data to refine the distribution of these vegetation 39 types across the Great Basin. However, the summary of vegetation phenology by vegetation 40 types encountered two challenging questions: First, some scientists argued that there are no 41 realistic grass-dominated lands in the Great Basin. Second, grasses also exist in the interspace 42 areas of patchy shrublands. Thus, based on current NDVI data, it is challenging to separate 43 vegetation signal of grasses from those of shrublands. Later, when we repeat this study, we 44 ignored vegetation types and summarized NDVI only by the points considered in this study. 45 Based on our earlier study, it appeared that in some part of the northern Great Basin where 46

1 grasses might be dominant (e.g., especially invasive species cheatgrass, blue points in panel (b)

2 in the following figure), the magnitude of changing rates in vegetation greenness during the

3 study period were greater than those in the southern part of the study region, where shrubs are

dominant vegetation types.





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Figure. The potential distribution of shrub-dominated, grass-dominated and cheatgrassdominated lands in the US Great Basin.

Finally, when you describe changes in trends within the study period, have you used a trend change point detection method to infer that or is that just by eye? I would suggest that it should be based on an established method, and if so this needs to be detailed in the methods. Also it might be good to try and explain why this occurs in terms of any changes in driving variables (as this is already your aim).

Response: Similar to determining the long-term (30-year) trend, we also used the Kendall-Tau
approach to analyze the trend in different time intervals during the study period. The change
point was first determined by eye followed by a Kendall Tau trend analysis. We mentioned in the
methods section that the Kendall-tau approach for trend analysis was also applied to different
time-intervals during the study period 1982-2011.

24 Minor points:

P11389 Line 1: rather than saying e.g. forests and water for biotic and abiotic I would suggest
 that it's more accurate to say (biological versus physical).

Response: We changed "biotic (e.g., forests)" to "biological" and "abiotic (e.g., water) to
"physical" in the revised manuscript.

Line 9: Might be good to suggest what the implications are for the terrestrial C, W, E, e.g. it defines the period of C uptake, or the partitioning of sensible and latent heat flux etc.

Response: We added some examples in the related text to demonstrate the implications. Line 23: See also Poulter et al. 2014 Nature doi: 10.1038/nature13376 and Ahlstrom et al. 2015 Science 348, 895-899 Response: We cited these two papers in the revised version. Line 26: Could you give an example of the consequences for ecosystem services to provide some context. Response: We provided two examples of ecosystem services. They are maintaining livestock and freshwater. P11391 Line 24: Not sure Botta is a good reference for the fact that every every forests have little to no seasonal cycle, even though in her paper there's no evergreen model because of that reason. Response: Thanks for your good comments. We have tried to check but failed to find other references that might be better to cite here. Botta et al. (2000) clearly stated that "We excluded the evergreen broadleaf forest biome from our analysis as it has little or no leaf seasonal cycle". It is why we cited this paper here. P11395 Line 6: What is the mix of vegetation in the pixels? It might be nice to know how much the signal is affected by trends in a certain vegetation type to try to understand the processes at play. Response: This is a very good but very tough question. Without additional and detailed field study, it is so hard to answer this question. The NDVI data used in this study depict the overall greenness at each grid cell. The data do not provide information about how different vegetation types affect vegetation greenness in a grid cell. P11397 Line 21: Sentence restructure: Something like In spring 12% of the points exhibited a significant negative trend from 1982-2011, and most. . . Response: We revised this sentence following your suggestion. P11400 Line 17: Fensholt (2012, not 2011) at least also suggests this might be due to precipitation and not just warming (actually they state "widely different explanations"), unless you're suggesting it's an indirect of warming, but I'm not sure we know that? I think it would be useful to add that in. Response: We added Fensholt et al, 2012 in the related citations. P11401 Line 1: The discrepancies may also be due to different data processing and time period considered?

1 Response: Following your suggestion, we revised this sentence.

P11405 Line 4: I would be surprised if deep roots are the cause for grasses. Are there any studies
that have looked at this for these regions – any observations of soil moisture or groundwater?
Also deep roots would alleviate any effect of higher temperatures on summer NDVI that you

6 appear to see.

7 Response: For grasses, we are not quite sure either. For shrubs, theoretically, the deeper the

8 roots are, the more likely the plants are able to take up soil water from the saturated zone, or

9 deeper in the vadose zone, and thus moderate the effects of droughts on foliage and vegetation

10 greenness (e.g., Smith, S. D., Monson, R. K. & Anderson, J. E. Physiological Ecology of North

11 American Desert Plants [Springer, Berlin, 1997; Whitford WG 2002 Ecology of Desert Systems,

12 Elsevier Science, London, 345 pp]).

Line 19: I believe there are quite a number of studies looking at the invasions of non-native species in grasslands of the US? Could these help your discussion here? Table 1: is STP/PSP one variable as a ratio?

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17 *Response: Yes, there were several studies focusing on effects of invasive species especially*

18 cheatgrass on vegetation phenology in the US Great Basin. We have cited some of these studies

19 in our manuscript (e.g., Bradley, B. A. and Mustard, J. F.: 2008, global change biology). We

20 also contacted some authors for potential vegetation data like the distribution of cheatgrass in

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the US great basin. However, it is challenging to separate signals of shrubs from that of grasses
without field observations or more detailed image studies. In addition, there is no precise

information about the distribution of invasive species in the Great Basin. These challenges

require additional studies. We revised the heading in Table 1 for clarification. Originally,

25 STP/PSP refers to the corresponding variable could be either STP or PSP.

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3 Anonymous Referee #2

5 Received and published: 3 October 2015

7 General Notes:

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8 As noted by the authors, the phenology of drylands is relatively understudied compared

9 to deciduous forests, despite the substantial role these ecosystems play in the global

- 10 carbon cycle. Here, Tang and colleagues utilize station meteorology and GIMMS NDVI
- 11 imagery to assess long-term trends in phenological indices (SOS, EOS, and GSL) and
- 12 vegetation greenness (mean NDVI) in the US Great Basin region, as well as the relative
- 13 importance of temperature and precipitation in explaining their interannual variability.
- 14 The central findings are that GSL has extended at the rate of 3 days per decade due to
- 15 delayed autumn senescence, driven largely by increases in mean seasonal temperature,
- 16 but variability in vegetation greenness is better explained by precipitation variabil-
- 17 ity, in particular preseason precipitation (DJF). The analysis is well devised, and the
- 18 paper is very well written. The paper would be improved, in my opinion, if the authors
- attempted to connect their results with the carbon cycle and/or future climate changes,even if it were only informed speculation. I also wonder about the extensive spatial
- averaging and the lack of analysis of local weather/phenology relationships (do the relationships)
- hold at the station-level?). Despite these shortcomings, I think this is a nice
- contribution to the literature and would support its publication.
- 24

25 *Response: Thanks for your positive comment. In terms of how shifts in vegetation phenology will*

- **26** affect or have affected carbon cycle and how future climate change will affect vegetation
- 27 phenology in the semiarid and arid ecosystems of the US Great Basin, additional study is needed
- 28 to answer these questions. As far as the relationship between vegetation phenology and local
- 29 weather at the station level is concerned, some of our results (e.g., Fig. 4b, c, d) suggest that the
- 30 basin-wide average relationship between vegetation phenology and regional climate change may
- 31 not always apply at the local scale due to the spatial heterogeneity of climate condition
- 32 (including both temperature and precipitation) across the study region.33

34 Specific Notes:

- Why would you consider both SOS_SSA and SOS_Spring models (e.g. Table 2)?
- 36 Since SSA is calculated over spring, summer, and autumn Temperatures, the difference
- 37 between Spring T and SSA are FUTURE temperatures, right?
- 38
- 39 *Response: The main reason for calculating the relationships between SOS and spring*
- 40 temperature as well as between SOS and SSA temperature is because changes in GSL are subject
- 41 to both SOS and EOS. Thus, quantifying the relationship between spring temperature and GSL
- 42 will help us understand how changes in spring temperature (e.g., spring warming) are likely to
- 43 affect GSL. Sorry, we are a bit confused about the meaning of the statement of "the difference
- 44 *between Spring T and SSA are FUTURE temperatures*".
- 45
- The rates of mean NDVI increase are quite small (e.g. 5e-4), and so would only
- 47 contribute to an increase of 0.015 over the 30 year period. This seems very slight, is it

ecologically significant? Of course, it is consistent with the magnitudes noted by other 1 authors like Fensholt. 2 3 Response: Thanks for coming up with such a very good and tough question. First, the 4 magnitudes of NDVI are between 0 and 1.0. In semiarid and arid ecosystems of the Great Basin, 5 the NDVI values of ecosystems at lower elevation zone are mostly less than 0.30. Generally, 6 because the magnitudes of NDVI values are low, the resulting changing rate from one year to the 7 8 next is also very small. Whether or not such small changes in NDVI values are ecologically 9 significant, we need to conduct additional study to answer it. However, a model-based study (Tang et al., 2015 in review by Ecohydrology) suggested that changes in leaf area index (LAI) in 10 semiarid and arid mountain watershed in the Great Basin can greatly affect soil moisture 11 12 condition and the exchange of water fluxes between the atmosphere and the land despite the 13 relatively low values in NDVI, indicating that even these small changes can have a significant 14 impact in arid ecosystems. 15 16 - How well do the splines fit? Sometimes they can go "off the rails" and interpolate 17 much higher/lower NDVI values, especially in the presence of missing data. 18 Response: Good question! In our study, because we focused on NDVI values from March to 19 November, missing data were rare. At each of the 4145 points considered in this study, time 20 series of bi-weekly NDVI values are generally continuous. Because NDVI values are continuous, 21 the interpolation of bi-weekly NDVI values into daily values by cubic spline functions rarely 22 caused the interpolated values to fall out of the range of original high and low NDVI values. 23 24 25 **Technical Notes** - P11388, L25: Since vegetation would presumably respond to climate change regardless 26 of its cause, I'd suggest "climate change" instead of "anthropogenic climate, 27 change" 28 29 *Response: Changed "anthropogenic climate change" to "climate change"* 30 31 - P11389, L8-9: Unclear what "consequent information" means here, perhaps: "Consequently, 32 phenological information has important applications..." 33 34 Response: Thanks! We changed "Consequent information" to "Consequent information – such 35 as climate change-associated shifts in vegetation phenology and biogeochemistry –" 36 37 - P11389, L22: "and ARE particularly sensitive" 38 39 Response: Thanks! We changed "particularly sensitive" to "are particularly sensitive". 40 41 42 - P11392, L1-5: Which version of the GIMMS dataset? 43 44 Response: We revised the related text. The data used in our study is GIMMS NDVI3g. 45 - P11393, L24: The acronym "SSA" was defined in the abstract, but not in the main 46

1	text before its use here, it wouldn't hurt to do so.
2	Demonstration II. do "CCA" and do line 14 on one of 11202. In the anticed management
3 1	Response: Actually, the SSA was defined in the 14 on page 11592. In the revised manuscript, we changed "considered the period of March to November (i.e. spring, summer, autumn and
4	hereafter SSA)" to "considered the period of March to November (i.e., spring, summer, dulumn and
6	
7 8	- P11397, L21: Change "points were exhibited" to "points that exhibited" or similar
9 10	Response: Thanks! We changed "points where exhibited" to "points that exhibited"
11 12	- P11399, L1: Probably not "surprising" since it was the implicit hypothesis
13 14	Response: We deleted "Surprisingly" in the revised manuscript.
15	- P11401, L4-7: Wouldn't these spatial differences argues for a more spatially explicit
16	analysis (i.e. less extensive spatial averaging)? If altering the study are slightly would
17	change the sign of a regression coefficient, and the inference based on that relationship,
18	what does that say about the robustness of the findings?
19	
20	Response: We agree with your comment. Due to the complexity of environmental factors in
21	affecting vegetation phenology, a more spatially explicit analysis is likely to help answer how
22	local environmental condition may affect vegetation phenology. To some degree, changing the
23	extent of study region is likely to alter the sign of relationship between climate and vegetation
24 25	phenology. Neverineless, our study jocused on regional-scale relationship between vegetation
25	phenology and climate change. Because of the homogeneity of regional warming and because
20	atmospheric circulation we believe that the overall relationship between vegetation phenology
27	and climate change we observed for the Great Basin is robust
20	and climate change we observed for the Great Basin is robusi.
29	- P11401 I 15: What is meant by "ameliorate soil moisture conditions"?
30	111401, 213. What is meant by amenorate son moisture conditions :
32	Response: Thanks! We changed "ameliorate soil moisture conditions" to "increase soil moisture
33	content"
34	
35	- P11402, L23-27: But you have the station-data to test whether or not the local trends
36	are consistent with their local climatic variation, right?
37	
38	Response: Yes, we do have field observations of time series daily precipitation. Our initial
39	analysis of daily precipitation across 100 field stations suggested that precipitation indeed varies
40	spatially in the study region. We are currently working on another paper focusing on the
41	variation of daily precipitation and precipitation extremes in the Great Basin. Even though we
42	acknowledge this to be an important point we felt it was outside the scope of our current paper
43	that deals with large-scale regional patterns
44	
45	- P11403, L1: Suggest changing "agreed well" to "were consistent" Saying that the observations

"agreed" with the ground observations implies that their interannual variations are consistent. The datasets could share a lack of long-term trend without "agreeing" at all. Response: Thanks! We changed "Agreed well" to "were consistent" in the revised manuscript. - P11403, L15-17: Stronger warming at higher latitudes may be only one of multiple factors leading to contrasting Northern Hemisphere SOS results, vegetation assemblages are also different, for instance. Response: Thanks for your good comments! - P11405, L17: Suggest changing "we are lack of" to "we lack" Response: We changed "we are lack of" to "we lack of" by deleting "are". - Table 1: There are two AIC columns with the heading: "STP/PSP", should one be "SMT/PSP"? *Response: Sorry for the confusion. Originally, the heading "STP/PSP" means that precipitation* may be either seasonal total precipitation or pre-season precipitation". We revised Table 1 for clarity. - Table 1: footnote: "minimum" would be better than "smaller" in this case since smaller could be interpreted as "closer to zero" rather than "most negative" Also on P11404 L25 Response: Thanks! For clarity, we changed "the smaller the AIC values are" to "the smaller the magnitude of the AIC value is". - Table 3: It's clear from Table 3's footnote, but not the text, that PSP refers to DJF precipitation. This should be in the text, in my opinion. Response: Thanks. PSP was defined as "Pre-season precipitation" in the main text (line 17 on page 11399 in the earlier version of this manuscript). In most cases, PSP refers to DJF (December, January and February) precipitation. However, there are cases where PSP refers to seasonal precipitation such as spring.

1	Trends-Trends and climatic sensitivity sensitivities of vegetation phenology in semiarid and
2	arid ecosystems in the U.S. Great Basin during 1982-2011
3	
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1 Abstract

2	We quantified the temporal trend and climatic sensitivity of vegetation phenology in dryland
3	ecosystems in the U.S. Great Basin during 1982-2011. Our results indicated that vegetation
4	greenness (Normalized Difference Vegetation Index, NDVI) in the Great Basin increased
5	significantly during the study period, and this positive trend occurred in autumn but not spring
6	and summer. Spatially, increases in vegetation greenness were more apparent in the northwestern,
7	southeastern, and eastern Great Basin but less apparent in the central and southwestern Great
8	Basin. In addition, the start of growing season (SOS) was not advanced while the end of growing
9	season (EOS) was delayed significantly at a rate of 3.0 days per decade during the study period.
10	The significant delay in EOS and lack of earlier leaf onset caused growing season length (GSL)
11	to increase at a rate of 3.0 days per decade during 1982–2011. Interestingly, we found that the
12	[interannual?] variation of mean vegetation greennessNDVI in calculated for the period of March
13	to November (spring, summer, autumn: SSA) was not significantly correlated with its-mean
14	surface air temperature measured during SSA but was strongly correlated with the its-total
15	amount of precipitation that fell in that period. Seasonally, the variation of mean vegetation
16	greenness in spring, summer, and autumn was mainly attributable to changes in pre-season
17	precipitation in winter and spring. Nevertheless, climate warming (0.6°C [?] from 1982 to 2011)
18	appeared to played a strong role in extending GSL that in turn resulted in the upward trend in
19	mean vegetation greennessNDVI during 1982–2011. Overall, our results suggested that changes
20	in wintertime and springtime precipitation played a stronger role than temperature in affecting
21	the interannual variability of vegetation greenness, while climate warming was mainly
22	responsible for the 0.02 [?] point increase in NDVI observed in Great Basin dryland ecosystems

- 1 during the 30-year period of upward trend in [the magnitudes of] mean vegetation greenness in
- 2 the dryland ecosystems during 1982 to –2011.
- 3 Keywords: Phenology, greenness, leaf senescence, growing season length, climate sensitivity,
- 4 dryland ecosystems

1 Introduction

2	Shifts in plant phenology (e.g., greenness and spring leaf onset) resulting from climate
3	change can affect the cycling of carbon, water, and energy between the biosphere and
4	atmosphere (Wu and Liu, 2013), the availability of biological and physical resources (White and
5	Nemani, 2011), and the best practices for managing these resources for production of fiber and
6	food to sustain human life (Butt et al., 2011). Quantifying the spatiotemporal dynamics of plants
7	phenology – such as long-term trend in vegetation greenness, the start of growing season (SOS),
8	end of growing season (EOS), and growing season length (GSL) – and their climatic sensitivity
9	can enable us to assess climate change impacts on terrestrial vegetation dynamics (Soudani et al.,
10	2011) and ecosystem biogeochemistry (Brown et al., 2010). Consequent iInformation – such
11	asabout climate change-associated shifts in vegetation phenology and biogeochemistry —in turn
12	has important implications (e.g., defining the period of carbon uptake) for more accurate
13	prediction of terrestrial water, carbon, and nutrient cycles in Earth system, climate, and
14	ecosystem models (e.g., Piao et al., 2011).
15	Existing phenological studies mostly focus on regions with low evergreen cover such as
16	temperate deciduous forests (e.g., Nagai et al., 2010) or where terrestrial ecosystems may be
17	particularly sensitive to climate warming such as boreal and arctic regions (e.g., Zhang et al.,
18	2011). Only Aa few studies have focused on quantifying plant phenological responses in
19	semiarid and arid (hereafter dryland) ecosystems to climate variability and recent climate
20	warming (e.g., Bradley and Mustard, 2008; Zhang et al., 2010; Fensholt et al., 2011). Although
21	terrestrial carbon sequestration was has been considered to be relatively low in dryland
22	ecosystems, these ecosystems cover almost 40% of Earth's land area (UNDP/UNSO, 1997) and
23	account for nearly 20% of the global soil carbon pool (Field et al., 1998; Lal, 2004). They also

1	may be buffering anthropogenic CO ₂ rise more than expected (Jasoni et al., 2005; <u>Hastings et al.</u>
2	2005; Wohlfahrt et al., 2008; Poulter et al. 2014; Ahlström et al., 2015;) and are particularly
3	sensitive to both climatic variation (Jasoni et al. 2005; Wohlfahrt et al. 2008) and increasing
4	atmospheric CO ₂ concentrations (<u>Jasoni et al., 2005;</u> Notaro et al., 2011 ; Poulter et al., 2014;
5	Ahlstrom et al., 2015). Hence, quantification of the responses of dryland plant phenology to
6	climate variability at the regional scale is needed to improve forecasting of shifts in ecosystem
7	functioning and consequences for ecosystem services including (e.g., maintaining-livestock
8	grazing, wildlife habitat, freshwater etc.and modulation of atmospheric CO ₂) that drylands
9	provide.
10	Furthermore, climate warming has been widely accepted as the major driver responsible for
11	the general increase in vegetation greenness, the earlier SOS, the delayed EOS, and the extension
12	of GSL that have occurred in the Northern Hemisphere during the past few decades (e.g., Piao et
13	al., 2011; Hmimina et al., 2013). These findings, though, mainly apply to mesic ecosystems
14	where water is often not limiting for vegetation growth. In dryland ecosystems, water is scarce
15	and the availability of water strongly controls plant seed germination, growth, and reproduction
16	(e.g., Bradley and Mustard, 2005). Although some studies indicated that precipitation plays an
17	important role in affecting vegetation greenness (e.g., Wu and Liu, 2013) and SOS (e.g., Cong et
18	al., 2013) in temperate deserts, it is still unclear if the role of precipitation is as strong $as_{\underline{a}}$ or even
19	stronger than, that of temperature in controlling some aspects of plant phenological dynamics in
20	dryland ecosystems. Improved understanding of the role of precipitation in affecting or
21	controlling plant phenology in dryland ecosystems is critical for accurate quantification of
22	terrestrial carbon, water, and plant community dynamics under changing climatic conditions

1	Therefore, the objectives of this study were to utilize the dryland ecosystems at lower
2	elevation zones of the U.S. Great Basin (Fig. 1) to (i) quantify long-term trends in mean
3	vegetation greenness (represented by Normalized Difference Vegetation Index (NDVI)), SOS,
4	EOS, and GSL in the dryland ecosystems that may have occurred during the most recent 30
5	years of climate warming; (ii) explore the spatial variation of long-term trends in vegetation
6	greenness; (iii) and examine the climatic sensitivity of trends and variation of vegetation
7	phenology in the study region. To meet these objectives, we utilized satellite-based NDVI data
8	because they enable us to quantify the synoptic and landscape pattern of vegetation phenology
9	(White et al., 2009) as well as its long-term temporal dynamics (Studer et al., 2007). Time series
10	of weather records (temperatures and precipitation) were used to analyze climatic sensitivities of
11	vegetation phenology in the study region.

12 2 Materials and Methods

13 2.1 Study region

The Great Basin is located in the western United -States- and encompasses the majority of 14 Nevada (NV), western Utah (UT), and parts of California (CA), Oregon (OR), Idaho (ID), 15 Montana (MT), and Arizona (AZ) (Fig. 1a). It is bordered by the Sierra Nevada Range on the 16 west, the Rocky Mountains on the east, the Columbia Plateau to the north, and the Mojave and 17 Sonoran deserts to the south. The hydrographically defined Great Basin includes the northern 18 Mojave Desert (Grayson, 2011). Lying in the rain shadow of the Sierra Nevada mountain range, 19 the Great Basin is the driest region in the U.S. and experiences extremes of weather and climate 20 21 that are not normally found elsewhere in the U.S. (Houghton et al., 1975). Most precipitation 22 falls in the winter. Climate conditions inside the Great Basin vary by elevation and latitude, and 23 most of the Basin experiences a semiarid or arid climate with warm summers and cold winters.

1	Land cover types in the Great Basin are diverse because of topographic and local climatic
2	heterogeneity. The predominant flora in the Great Basin consist of shrubs such as Artemesia
3	tridentata (sagebrush), Ericameria nauseosa (rabbit brush), Sarcobatus vermiculatus
4	(greasewood); grasses such as Achnatherum hymenoides (Indian rice grass), Bouteloua
5	curtipendula (Sideoats grama); evergreen trees such as Pinus monophylla (pinyon pine) and
6	Juniperus osteosperma (Utah juniper); as well as invasive species including Bromus tectorum
7	(cheatgrass). In contrast to shrubs and grasses that are mostly present in valleys, evergreens are
8	mainly located in mountain ranges and at higher elevations. Because evergreen forests have little
9	or even no visible leaf seasonal cycle (Botta et al., 2000), they were excluded from this study
10	(see below).
11	2.2 Satellite-based vegetation indices and data processing
12	We used the global inventory monitoring and modeling studies (GIMMS) NDVI3g data to
13	examine the long-term trends in vegetation greenness and phenology. The GIMMS NDVI data
14	were derived from the NOAA Advanced Very High Resolution Radiometer (AVHRR) series
15	satellites (NOAA 7, 9, 11, and 14) and span from January 1982 to December 2011 (Tucker et al.,
16	2005). These data are at bi-weekly temporal and 8 km spatial resolution. The data also-were
17	corrected to remove known non-vegetation effects caused by sensor degradation, clouds, and
18	stratospheric aerosols loading from volcanic eruptions (Tucker et al., 2005). The GIMMS NDVI
19	data have been widely used to quantify long-term trends in vegetation phenology and its
20	relationships to climatic variability at global and continental scales (e.g., Brown et al., 2010;
21	Zhang et al., 2010; Cong et al., 2013). Given that snow cover can affect NDVI values, our
22	analysis excluded winter (December, January and February) and only considered the period of
23	March to November (i.e., hereafter SSA).

1	To accurately quantify how vegetation phenology in the Great Basin may have changed and
2	responded to climate change during the study period, we refined our study areas based on the
3	Global Land Cover Facility (GLCF) 8 km land cover data (Hansen et al., 2000) and the National
4	Land Cover Database (NLCD) 2001 (Homer et al., 2007). We first excluded areas where
5	evergreen trees predominated in both GLCF and NCLD 2001. In addition, we excluded lakes,
6	urban areas, and cultivated lands defined in either GLCF or NLCD 2001, the phenology of which
7	depends largely on management practices (i.e., irrigation) and crop types. As a result, only lands
8	areas where shrubs/grasses were predominant in both GLCF and NLCD 2001 (Fig. S1 in
9	Supporting Information) were considered. Finally, we excluded areas located at relatively high
10	elevations (>2100 m), and only selected those at lower elevations (<2100 m; areas where over 85%
11	of shrubs and grasses are located according to GLCF data) for our analysis (Fig. S1). Fig. 1b
12	shows the distribution of NDVI points considered in this study.
13	2.3 Weather data and processing
14	We generally followed the same procedure of acquiring and processing weather data as
15	described in Tang and Arnone (2013). Briefly, we collected time series of daily minimum and
16	maximum temperatures as well as total precipitation from 126 weather stations that are or were
17	historically located within the Great Basin. These stations included the Cooperative Observer
18	Program Stations (COOP), the Remote Automated Weather Stations (RAWS), the SNOwpack
19	TELemetry (SNOTEL) weather stations, and Nevada Test Site (NTS) stations (Fig. 1a). The
20	selection of 126 stations was based on two criteria: first, selected stations had to have at least 24
21	years of records (80% of coverage of our study period) for each of 12 months during the period
22	of interest in this study; second, selected stations had to be located near selected NDVI points

23 (Fig. 1b). Stations located inside developed areas (e.g., residential), and cultivated land or near

urban areas/cities were excluded to maximize the accuracy of climatic sensitivity analysis of
 vegetation phenology.

In addition, fFor each of the selected stations during the period of interest, daily weather 3 records that exceeded the long-term (1982-2011) mean of all available records from that station 4 by four standard deviations (for temperature) or greater than 500 mm (for precipitation) were 5 manually checked or removed on a case-by-case basis (Tang and Arnone, 2013). We plotted and 6 7 visually compared derived time series of monthly minimum and maximum temperatures at each 8 station with those from neighboring stations to further check data inhomogeneity (e.g., Peterson et al., 1998). Daily mean temperature for each station and each day was calculated as the mean of 9 10 recorded daily minimum and maximum temperatures. Based on these daily values, we calculated 11 mean temperatures for each month, season, and SSA. We used daily total precipitation values 12 from each station to calculate precipitation sums for each month, season and SSA at each of the selected stations. 13 2.4 Characterization of temporal dynamics and climatic sensitivities of plant phenology 14 15 To quantify long-term trends in vegetation greenness, SOS, EOS, and GSL, we first interpolated the bi-weekly series GIMMS NDVI3g data for all points considered in this study 16 into daily time step values using a cubic spline interpolation approach. Based on interpolated 17 daily NDVI values, we followed the midpoint-pixel method (White et al., 2009) to define SOS, 18 EOS, and GSL for each NDVI point (Fig. 1b). Instead of using a global threshold, the midpoint-19 pixel approach uses a locally tuned NDVI threshold to define SOS. This metric has been 20 21 demonstrated (e.g., White et al., 2009) and also initially tested (see below for detail) to be 22 suitable for semiarid and arid regions. In the midpoint-pixel approach, the state of the ecosystem 23 is indexed by transforming the NDVI to a 0 to 1 NDVI_{ratio} as:

1
$$NDVI_{ratio} = \frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}}$$

where NDVI is the interpolated daily NDVI value in a year; and $NDVI_{max}$ and $NDVI_{min}$ are the 2 maximum and minimum of the NDVI curve. Thus, SOS can be defined as the day of year when a 3 NDVI_{ratio} of 0.5 is exceeded because the 0.5 value is often considered to correspond to timing of 4 the most rapid increase in NDVI or to the initial leafing of the overstory canopy (White et al., 5 2009). In our study, we defined SOS as the date in a year when the daily NDVI_{ratio} becomes 6 greater than 0.5 for six consecutive days in ascending order, and EOS as the date in a year when 7 the daily NDVI_{ratio} becomes less than 0.5 for six consecutive days in descending order. Annual 8 GSL was calculated as the difference between EOS and SOS. Our initial comparison of SOS 9 based on the midpoint-pixel method with that based on observed breaking leaf buds data (USA 10 National Phenology Network (USA-NPN), 2010) for the study region justified the suitability of 11 12 this metric in the study region (Fig. S2). The nonparametric Kendall's tau (τ) based slope estimator (Sen, 1968) was used to compute 13 long-term (1982-2011) or short-term (i.e., a shorter period during 1982-2011) trends in four 14 phenological indices: vegetation greenness, SOS, EOS, and GSL based on their Basin-wide 15 averaged anomalies. We also used this metric to calculate the trends of vegetation greenness at 16 each of NDVI points to examine the spatial variation of trends of vegetation greenness during 17 18 1982–2011. The Kendall's tau method does not assume a distribution for residuals and thus is insensitive to the effect of outliers in time-series data. The two-tailed P-values at the 95% 19 20 (significant) or 90% (marginal significant) confidence levels were used to test the significance of trends. 21

(1)

This study followed the same procedure described in Tang and Arnone (2013) to calculate a single value for each phenological index for the entire Basin. Briefly, we first divided the basin

1	into $1.34^{\circ} \times 1.34^{\circ}$ boxes to make a total of 37 boxes, each of which (except one) contained at
2	least one weather station (Fig. 1a). We calculated anomalies for each index for each month,
3	season, and SSA at each location (e.g., a NDVI point) against its 30-year arithmetic mean,
4	respectively. We then averaged all anomalies within a box to obtain the box anomaly for each
5	index for each month, season, and SSA. Finally, the resultant box anomalies for each index are
6	averaged to obtain its Basin-wide average. The goal of using this approach was to minimize
7	effects of clustered points on the Basin-wide averaged values for each month, season, and SSA.
8	The above approaches outlined above also were also applied to temperature and precipitation
9	indices.
10	Based on basin-wide averaged anomalies, we analyzed the sensitivity of vegetation
11	phenology to changes in temperature and precipitation through the univariate linear regression
12	approach largely because temperature and precipitation correlate/interact with each other. The
13	purpose of this analysis iwas to examine which variable alone (temperature or precipitation) can
14	better explain the interannual variability of vegetation phenology during 1982–2011. The
15	Akaike Information Criterion (AIC; Akaike, 1974) was used to determine the goodness fit of a
16	univariate linear regression model. In addition, multivariate regression models based on
17	temperature, precipitation and their interaction were developed to analyze the contribution of
18	variation in temperature, precipitation and their interaction to the variations of vegetation
19	phenology during 1982–2011. We used the metric proposed by Lindeman, Merenda and Gold
20	(LMG; Grömping, 2006) to quantify the relative importance of each regressors (e.g., temperature,
21	precipitation and their product) in controlling the variation of vegetation phenology in the study
22	region. The LMG metric considers both the direct effects of an independent variable (e.g.,
23	temperature) on a dependent variable (e.g., greenness) and its indirect effects adjusted by other

independent variables (e.g., precipitation) in a multivariate regression model and thus is suitable 1 for comparing the contribution of variation in temperature and precipitation as well as their 2 interaction to variations in vegetation phenology. 3 4 **3** Results 5 3.1 Long-term trends in vegetation greenness and corresponding climatic conditions When averaged for the period of March to November (i.e., SSA), both mean NDVI and mean 6 7 surface air temperature in SSA in the dryland ecosystems increased significantly during the 8 period 1982–2011 (Fig. 2a, b) while total precipitation in SSA showed no significant trend during the study period (Fig. 2c). The rate of increase was about 5×10^{-4} (p<0.04) units per year 9 in NDVI and 0.2 °C (p<0.09) per decade in temperature during 1982–2011. Although mean 10 11 NDVI in SSA increased during the 1982–2011 period, this long-term positive trend contained shorter periods of increases or decreases in NDVI (Fig. 2a). For example, mean NDVI in SSA 12 13 decreased significantly (p<0.01) from 1986 to 1992 and then increased significantly (p<0.01) from 1992 to 1998 (Fig. 2a). Similarly, even though the long term positive trend in mean surface 14 air temperature showed a long-term positive trend and total precipitation showed no trend in total 15 precipitation in SSA both air temperature and precipitation also comprised displayed shorter 16 periods of significant increases or decreases (Fig. 2b, c). 17 18 Seasonally, seasonal mean vegetation greenness NDVI in autumn (Fig. 3c) increased 19 significantly (p<0.01) while greenness-NDVI in spring and summer (Fig. 3a, b) had-showed no 20 significant (p>0.13) trend during the 1982–2011 period. Seasonal mMean temperature in spring 21 and autumn (Fig. 3d, f) showed no significant (p>0.19) trend while seasonal-mean temperature in summer (Fig. 3e) increased significantly (p<0.02) during the <u>30-year</u> period <u>1982–2011</u>. 22

23 Compared to seasonal mean temperatures In contrast, seasonal-total precipitation in spring,

1	summer and autumn had-showed no significant trends (p>0.13) from 1982 to 2011 (Fig. 3g, h, i).
2	[What about winter precipitationpre-growing season?? Would be good to include this.]
3	During the 30-year observation period, The seasonality of NDVI, temperature, and
4	precipitation also varied at different time intervals during 1982-2011showed a number of
5	shorter-term trends that differed by season. For example, mean springtime NDVI decreased from
6	1986 to 1992 (Fig. 3a) whereas mean autumn NDVI increased from 1992 to 1998 (Fig. 3c). In
7	addition, although summertime NDVI showed no significant trend during the period 1982-2011,
8	it decreased significantly (p<0.01) from 1982 to 1994 and from 1995 to 2008 (Fig. 3b).
9	3.2 Spatial heterogeneity of long-term trends in vegetation greenness
10	Our results indicated that mean <u>SSA</u> NDVI in <u>SSA</u> in 39% of the total points (4154)
11	considered in this study had significant (p<0.05) predominantly positive trends during 1982-
12	2011. These points with significant trends were concentrated located in the northwestern,
13	southern, and eastern Great Basin (Fig. 4a). The rates of increase in mean NDVI in SSA also
14	increased as latitude and longitude increase (Fig. S3). In the central Great Basin, points showing
15	significant long-term trends in NDVI were sparse (Fig. 4a). In addition, both positive and
16	negative trends in mean NDVI in SSA were observed. The number of points where NDVI had a
17	positive trend, however, was triple (30%) of those showing a negative trend (10%). The points
18	with a positive trend, which were concentrated in the southwestern corner part of the study
19	region or areas near the southern part of Sierra Nevada Mountains and the Death Valley. Overall,
20	points showing significant trends in NDVI in the Great Basin were dominated by the positive
21	trend during the 1982-2011 period (Fig. 4a), especially in northwestern, eastern, and
22	southeastern Great Basin.

1	Seasonally, the areas where springtime mean NDVI exhibited a positive trend from 1982 to
2	2011 only accountsed for 11%, most of which occurred in the northwestern and eastern Great
3	Basin (Fig. 4b). In the southeastern Great Basin, however, there was still a large portion of areas
4	where NDVI in spring that showed a significant positive trend (Fig. 4b). In addition, in spring 12%
5	of all the total points exhibited a significant negative trend from 1982 to 2011 and most of these
6	points were distributed along a corridor that extends from southwest to northeast of the Great
7	Basin or from areas near the eastern side of the Sierra Nevada mountains to the central and
8	northern Great Basin (Fig. 4b).
9	Summertime mean NDVI showed a significant positive trend in only 9% of the total points
10	considered in this study, and these points were scattered across the Great Basin (Fig. 4c). In 15%
11	of areas considered in this study, summertime mean NDVI decreased during 1982-2011 (Fig.
12	4c), and most of these points were concentrated in the southern and southwestern Great Basin
13	(Fig. 4c) and near the eastern side of the Sierra Nevada mountains. Autumn mean NDVI
14	increased in 31% of areas during the years 1982-2011 and these increases mostly occurred in the
15	northwestern, eastern, and southeastern Great Basin (Fig. 4d). As in other seasons, there still
16	were points where autumn vegetation greenness decreased significantly during the 1982-2011
17	period, but these points were less than 9% of the total points considered in our study (Fig. 4d)
18	and mostly concentrated near the eastern side of the Sierra Nevada Mountains.
19	3.3 Variation of SOS, EOS, and GSL in the Great Basin
20	Based on the GIMMS NDVI data, the values of the start of growing season (SOS) in
21	the viewed across the dryland ecosystems of the Great Basin showed no significant (p=0.59)
22	trend during 1982–2011 (Fig. 5a), indicating that spring leaf onset was not significantly
23	advanced changed during the study period. In contrast, the end of growing season (EOS)

1	increased significantly at a rate of 3.0 (p<0.002) days per decade during 1982–2011 (Fig. 5b),
2	suggesting that the timing of leaf senescence in the dryland ecosystems was delayed significantly
3	during these years. The non-significant trend toward earlier leaf onset and a significant delay in
4	leaf senescence extended the growing season length (GSL) at a rate of 3.0 (p<0.05) days per
5	decade in the dryland ecosystems during 1982–2011 (Fig. 5c).
6	In addition to these 30-year long-term trends, we observed significant interannual variations
7	in these phenological indicators. For example, the SOS varied on average from Julian day 90 to
8	111-Julian days, EOS varied from Julian day 271 to 295-Julian days, and GSL varied from Julian
9	day 164 to 196 days. Also, the timing of leafout and leaf senescence, as well as GSL, did not
10	change monotonically during the 30-year observation period. We also observed sshorter-term
11	(decadal or sub-decadal) trends-within the 30-year observation periodwere evident however. For
12	example, SOS decreased significantly during the 1982–1990 period while but increased
13	significantly during the 1994–2011 period (Fig. 5a).
13 14	significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin
13 14 15	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA
13 14 15 16	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower
13 14 15 16 17	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower elevation ecosystems dominated by shrubs and grasses (Fig. 6a). In contrast, the interannual
13 14 15 16 17 18	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower elevation ecosystems dominated by shrubs and grasses (Fig. 6a). In contrast, the interannual variability of mean annual SSA NDVI in SSA was significantly and positively correlated with
13 14 15 16 17 18 19	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower elevation ecosystems dominated by shrubs and grasses (Fig. 6a). In contrast, the interannual variability of mean annual SSA NDVI in SSA was significantly and positively correlated with the variation of its total annual SSA precipitation (Fig. 6b). Vegetation greenness (NDVI) tended
13 14 15 16 17 18 19 20	 significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower elevation ecosystems dominated by shrubs and grasses (Fig. 6a). In contrast, the interannual variability of mean annual SSA NDVI in SSA was significantly and positively correlated with the variation of its total annual SSA precipitation (Fig. 6b). Vegetation greenness (NDVI) tended to increased by 2.0 x10⁻⁴ (p<0.02) NDVI units per year when-while total annual SSA
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13 14 15 16 17 18 19 20 21 22 23	significantly during the 1994–2011 period (Fig. 5a). 3.4 Climatic sensitivities of vegetation greenness in the Great Basin There was no significant relationship (p=0.53) between the variation of mean annual SSA NDVI and mean annual SSA surface air temperature in SSA for the non-evergreen lower elevation ecosystems dominated by shrubs and grasses (Fig. 6a). In contrast, the interannual variability of mean annual SSA NDVI in SSA was significantly and positively correlated with the variation of its total annual SSA precipitation (Fig. 6b). Vegetation greenness (NDVI) tended to increased by 2.0 x10 ⁻⁴ (p<0.02) NDVI units per year when while total annual SSA precipitation in SSA increased by and average of 1% per year (about 2.83 mm year ⁻¹). The calculated AIC values (The smaller the AIC value is, the better a univariate regression model fits; Fig. 6) also indicated that the interannual variation of in total SSA precipitation can better

1	explain <u>ed</u> the interannual variability of observed in mean vegetation greenness in SSA <u>NDVI</u>		
2	during the 1982–2011 period.		
3	Further analyses based on the long-term trends of both mean <u>annual NDVI</u> and temperature		
4	in SSA suggested, however, that the positive trend of increase in mean annual SSA temperature		
5	in SSA duringobserved 1982–2011 (Fig. 2b) was mainly responsible for the upward trend in the		
6	magnitudes of increase in mean annual [SSA?] NDVI (Fig. 6c), which increased by 0.01		
7	(p<0.001) units per year when while the magnitude of mean annual SSA temperature increased		
8	by 1°C. In contrast, the analyses based on the trends of both mean <u>annual SSA</u> NDVI and <u>mean</u>		
9	total annual [SSA] precipitation in SSA indicated that precipitation did not play a significant		Formatted: Strikethrough
10	(p=0.64) role in leading to causing the long-term upward trend in the magnitudes of mean annual	_	Formatted: Strikethrough
11	<u>SSA</u> NDVI <u>seen</u> during the study period (Fig. 6d).		
12	Seasonally, the Iinterannual variability of in mean summertime mean NDVI was strongly and		Formatted: Strikethrough
13	negatively related to the variation of summertime mean temperature (p<0.02) but was not		
14	significantly correlated with the variation of summertime total precipitation (Table 1). In spring		
15	and autumn, the variation of seasonal mean NDVI was not significantly (p>0.15) related to the		
16	variations of in both either seasonal mean temperatures (Fig. 7a) and or seasonal total		
17	precipitation, respectively (Table 1-and Fig. 7a). Nevertheless, the long-term positive trend of		
18	mean NDVI in autumn was significantly correlated with the upward trend of autumn temperature		
19	although the trend in autumn temperature was statistically-nontsignificant (Fig. 3c and Fig. 7b).		
20	Compared to temperatures, tThe variation of Mean summertime mean-NDVI was positively	_	Formatted: Strikethrough
21	related to pre-growing season springtime precipitation sums (PSP) in the spring (p<0.001).	_	Formatted: Strikethrough
22	however while the variation of seasonal mean spring NDVI was not significantly correlated with	<	Formatted: Strikethrough
23	pre-growing season precipitation in spring and mean autumn NDVI was not significantly		Formatted: Strikethrough

1	correlated with was not significantly correlated with its pre-season precipitation in winter and	
2	summer precipitation, respectively (Table 1). In addition, the variation of seasonal mMean	
3	summertime and mean autumn NDVI were both strongly correlated with wintertime	
4	precipitationin summer and autumn also was strongly correlated with the variation of wintertime	
5	precipitation (Fig. 8). Overall, the calculated AIC values (Table 1) suggested that precipitation in	
6	winter and spring played a more important role than temperature in controlling the interannual	
7	variability of seasonal-mean spring, summer, and autumn vegetation greenness in spring,	
8	summer, and autumn-(Table 1).	
9	3.5 Climatic sensitivities of vegetation phenology in the Great Basin	
10	Our results indicated that the interannual variability of SOS was significantly (p<0.001)	
11	related to the variation of mean spring temperatures during the study period (Table 2). The	
12	timing of spring leaf-out tended to occur earlier by 2.7 days per year when springtime mean	
13	temperature increased by 1 °C (Table 2). In contrast, the interannual variability of EOS was not	
14	significantly (p=0.43) correlated with the variation of seasonal mean temperature in autumn	
15	during the study period (Fig. 7c). As a result, the interannual variation of GSL was positively	
16	correlated with the variation of mean temperature in spring and SSA_{2} although the correlation in	
17	spring was only marginally significant (p<0.10) at the 90% confidence level.	Formatted: Strikethrough
18	Although the variation of annual EOS was not significantly correlated with the variation of	
19	mean <u>autumn</u> temperature in autumn-(Fig. 7c), the <u>30-year</u> trend of in EOS was significantly	
20	(p<0.001) correlated with the trend of mean temperature in autumn during 1982–2011 (Fig. 7d).	
21	Similarly, although the variation of GSL was not significantly correlated with the variation of	
22	mean temperature in autumn (Fig. 7e), the trend of GSL was significantly (p<0.001) correlated	
23	with the trend of mean temperature in autumn (Fig. 7f). These <u>results</u> suggested that the upward	

trend in autumn temperature (although non-significant statistically) was responsible for the 1 trends of delayed EOS and extended GSL during 1982-2011 we observed in the US Great Basin. 2 4 Discussion 3 4.1 Long-term trends in vegetation greenness in the Great Basin 4 The increase in mean vegetation greenness in SSA we observed during 1982-2011 in the 5 dryland ecosystems in the Great Basin (0.015 NDVI units?) was consistent with reported trends 6 7 for other-similar ecosystems worldwide. Fensholt et al. (2012) suggested that semi-arid areas 8 across the globe experienced an increase in vegetation greenness of about 0.015 NDVI units on average during 1981-2007. Zhang et al. (2010) indicated that growing season NDVI in 9 10 grasslands in southwestern North America increased from 1982 to 2007. In arid environments of China, an increase in monthly average NDVI measured during the growing season also 11 12 increasedalso was_observed-during 1982-1999 (Piao et al., 2011). These trans-Northern-Hemispheric findings may have resulted from worldwide warming that has occurred during the 13 last few decades (e.g., Menzel et al., 2011; Zeng et al., 2011; Fensholt et al. 2012). In fact, 14 although the interannual variability of mean NDVI in SSA was not significantly correlated with 15 the variation of mean surface air temperature, the warming trend we observed in autumn (Fig. 3c) 16 was likely the major drivers responsible for the significant positive trend we measured in of GSL 17 (Fig. 7f), which in turn resulted in the 30-year positive trend in mean NDVI values in SSA (Fig. 18 9b) we measured observed in the dryland ecosystems in of the U.S. Great Basin. 19 Our results, however, contrast with those of Zhang et al. (2010) who reported both a negative 20 trend in NDVI from 1982 to 2007 in shrublands in southwestern North America, as well as an 21 oscillation in NDVI with increases observed from 1982 to 1993 and stronger decreases from 22 23 1993 to 2007. These apparent discrepancies may be attributed to differences in both time periods

1	considered and the spatial extent of the study regions (the Great Basin vs. southwestern North
2	America) and suggest that dryland ecosystems in more northern regions of the arid western U.S.
3	may respond differently to warming trends than those distributed in more southern regions of the
4	arid U.S. as indicated in our study (e.g., Fig. S3a). Such regional differences are actually
5	common (e.g., Jeong et al., 2011) and may be attributableed to latitudinal differences in solar
6	radiation and climate conditions such as decreasing temperature distribution (it decreases as with
7	increasing latitude increases, Fig. S4a).
8	The non-significant relationship between the variations of seasonal mean NDVI and mean
9	temperature in autumn in the dryland ecosystems suggested that other factors also played an
10	important role in regulating the interannual variability of vegetation greenness in autumn. The
11	Mmultivariate regression analyses suggested that precipitation in winter and autumn, as well as
12	mean temperature in SSA, are-were responsible (at the 98% confidence level) for the interannual
13	variability of mean NDVI in autumn (Table 3). Increases in surface air temperature [in autumn?]
14	can extend GSL (Fig. 8a) while and this temperature effect may be amplified if increaseding
15	precipitation can enhances soil moisture-water content. This combination is would likely to
16	stimulate vegetation growth <u>later into</u> autumn than under drier conditions. The significant
17	positive relationships between trends in autumn temperature and GSL as well as between trends
18	in autumn temperature and NDVI indicated that the warming in autumn (although not
19	statistically significant) was responsible-likely a major modulating factor for the long-term
20	upward trend of seasonal-mean autumn NDVI in autumn in the study region.
21	The no-absence of an observable trend in mean summertime mean-NDVI may have been
22	caused by the combination of an increase in summertime temperature and no change in
23	precipitation resulted from increase in summertime mean temperature (Fig. 3e) while

1	precipitation in summer had no positive trend (Fig. 3h). This combination of conditions may
2	have led to greater limitations (e.g., increased heat stress and deteriorated and resulting soil
3	moisture limitations) on plant growth in summer. In aAdditionally, the strong and negative
4	relationship we saw between the variations of mean temperature and NDVI in summer
5	contributed to the non-significant relationship between mean temperature and NDVI in SSA (Fig.
6	6a). The no-absence of a trend in mean springtime NDVI may have been caused resulted from
7	byresulted from the a lack of trend variation of in seasonal mean springtime temperature in
8	spring,-which did not increase significantly during the study period (Fig. 3d). Overall, the
9	significant and 4 non-significant relationships we quantified between mean-NDVI and total
10	precipitation ⁴ and between NDVI and mean-temperature respectively induring SSA (Fig. 6a)
11	suggestsed that changes in precipitation played a more important role than temperature in
12	controlling the interannual variability of mean vegetation greenness at lower elevation zones of
	the U.S. Creet Desig
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13 14	4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin
13 14 15	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and
13 14 15 16	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and
13 14 15 16 17	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern
13 14 15 16 17 18	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern Great Basin, temperature was lower compared to other regions and typically-low enough to
13 14 15 16 17 18 19	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern Great Basin, temperature was lower compared to other regions and typically-low enough to limits vegetation growth in spring (ref.). Thus, it was not surprising that the warming trends that
13 14 15 16 17 18 19 20	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern Great Basin, temperature was lower compared to other regions and typically-low enough to limits vegetation growth in spring (ref.). Thus, it was not surprising that the warming trends that we found appeared to more strongly benefit vegetation growth more at higher latitudes than it
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13 14 15 16 17 18 19 20 21 22	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern Great Basin, temperature was lower compared to other regions and typically-low enough to limits vegetation growth in spring (ref.). Thus, it was not surprising that the warming trends that we found appeared to more strongly benefit vegetation growth more at higher latitudes than it did at lower latitudes in the Great Basin, especially in spring and autumn (Fig. S4a). Zhu et al. (2011) also found that the spatial pattern of vegetation phenology in North America depended
13 14 15 16 17 18 19 20 21 22 23	 4.2 Spatial heterogeneity of trends in vegetation greenness in the Great Basin The trend of increasinge in the temporal positive trend in NDVI with time as latitude and longitude increase (longitude is negative, Fig. S3) likely was a resulted of from temperature and precipitation gradients along the latitudinal and longitudinal directions (Fig. S4). In the northern Great Basin, temperature was lower compared to other regions and typically-low enough to limits vegetation growth in spring (ref.). Thus, it was not surprising that the warming trends that we found appeared to more strongly benefit vegetation growth more at higher latitudes than it did at lower latitudes in the Great Basin, especially in spring and autumn (Fig. S4a). Zhu et al. (2011) also found that the spatial pattern of vegetation phenology in North America depended strongly on latitude. In additionFurther, the more spatially uniformity increases in NDVI the

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1	temporal positive trends we observed in autumn (Fig. 4d) may have occurred as a result of
2	relatively uniform precipitation generated by large-scale frontal systems, which generally start
3	from October and can create relatively uniform water additions to the entire region during the
4	autumn (Weiss et al., 2004).
5	-In the absence of these large regional inputs of precipitation, we expected that the temporal
6	trend in NDVI weould be spatially more variable across the Great Basin (Bradley and Mustard,
7	2008; Atkinson et al., 2011) than we actually observed (i.e., most points in Fig. 4a are green
8	showing significantly positive trends).
9	The phenological cycle of leaf onset and senescence, and effects of climate on vegetation
10	greenness, are vegetation- and location-dependent (Atkinson et al., 2011). In the western U.S.,
11	topography strongly modulates temperature and precipitation (Hamlet et al., 2007), and local-
12	scale processes – such as cold air drainage flow or the trapping of cold dense air masses by
13	mountainsrelief — can cause surface climate conditions to vary through space (Daly et al., 2010;
14	Pepin et al., 2011). Because of the spatial heterogeneity of precipitation timing and magnitude,
15	and because historical trends in temperature at the local scale also varied across the Great Basin
16	(Tang and Arnone, 2013), not all points showed significant positive or negative trends in
17	vegetation greenness during 1982-2011 (Figs. 4). Bradley and Mustard (2008) indicated that
18	trends in vegetation greenness in mountainous areas can significantly differ from those in valleys
19	in the Great Basin because valley ecosystems (possibly higher drought tolerance) tend to be more
20	resilient than montane ecosystems to severe drought. [But montane systems usually contain
21	mostly coniferous species which don't exhibit obvious phonological responses to climate
22	variations.]

4.3 Variation of SOS, EOS, and GSL in the Great Basin

1	The lack of a 30-year trend in SOS were was consistent well-with field observations in the
2	Great Basin during 1982-1994 (ref.?, or are you talking about your own data?), which also
3	showed no significant trend (p=0.40) (Fig. S2). Our estimates of SOS average 101 Julian days
4	during 1982-1994, which is only 2 days greater than that measured during ground-based on field
5	observations (99 Julian days; ref??). However, our <u>inability to finding of no_a</u> trend in SOS
6	contrasts results from with some other field observations, satellite-based data, and synthetic
7	studies <u>conducted</u> at regional or continental scales. For example, satellite observations revealed 3
8	to 8 days advance in spring phenology in northern latitude mesic ecosystems from 1982 to 1991
9	(Myneni et al., 1997), and a 6.4 day advance from 1982 to 1999 in Eurasian forests (Zhou et al.,
10	2001). Synthesis studies of long-term, in situ observations have identified a widespread trend
11	toward earlier spring in the northern hemisphere (e.g., Parmesan and Yohe, 2003). The
12	underlying reasons for these contrasting observations is that springtime mean temperature in the
13	Great Basin did not increase significantly during the study period (Fig. 3d) while spring warming
14	was more significant at high latitudes of the Northern Hemisphere.
15	Our finding of 3.0 days delay per decade in leaf senescence (EOS) in the Great Basin during
16	1982–2011 (Fig. 5b) is consistent with patterns from global studies, showing slight larger-scale
17	Northern-Hemispheric slight delays in EOS (0.3 to 1.6 days per decade; Menzel, 2002) and
18	larger North American delays in EOS (1.3 to 8.1 days per decade; Jeong et al., 2011; Zhu et al.,
19	2011) under warmer conditions. In addition, attribution of the extension of GSL mainly to
20	delayed leaf senescence, rather than to earlier leaf onset, also agrees with findings reported in
21	some previous studies (e.g., Zhu et al., 2011). Nevertheless, the non-significant relationship
22	between the variation annual of EOS and autumn temperature (Table 2) suggests that the
23	sensitivity of leaf senescence in dryland ecosystems to the variation of temperature may differ

1	from temperate and boreal forests where water availability is often not limited. The insensitivity
2	lack of sensitivity of EOS in the Great Basin to autumn temperature (Fig. 3c) might involve
3	interactive effects of temperature and soil water availability that signal plants to senesce in a way
4	that differs from temperate and boreal forests as demonstrated by the multivariate regression
5	analysis (Table 3, the three regressors for autumn NDVI are all marginally significant at the 90%
6	confidence level). In fact, the synoptic scale rainsfall events in autumn in these dryland
7	ecosystems can increase the variability of NDVI (Fig. S5), and thus likely alter the timing of leaf
8	senescence in autumn.
9	4.4 Climatic sensitivities of vegetation phenology in the Great Basin
10	Previous studies demonstrated that changes in plant phenology in the mid- and high-latitudes
11	of the Northern Hemisphere were primarily linked with to temperature variations due to
12	thethrough adaptive responses of vegetation to climate variability (e.g., Piao et al., 2011;
13	Hmimina et al., 2013)., and tThus earlier leaf onset in these regions was believed to result mainly
14	from spring warming (e.g., Kaduk and Los, 2011; Piao et al., 2011). These findings were are in
15	accordance with the our observed significant relationship we observed between the annual
16	variations of SOS and average annual spring temperature (Table 2). Our findings of The non-
17	significant relationships we observed between the annual variations of EOS and average annual
18	autumn temperature agreed well with some previously reported dataearlier findings from
19	European dryland ecosystems. For example, Menzel et al. (2011) reported weak and non-
20	significant that the correlations between leaf color change in fall and temperature trends for 14
21	European countries, with the lack of correlation was weak and non significant. As mentioned
22	above, this non significant relationship also may be attributed to the sensitivity of vegetation
23	growth in dryland ecosystems to synoptic rainfall events (Fig. S5).

1	Nevertheless, the significant positive relationships we observed between trends of autumn	
2	temperature and EOS ₂ as well as between the trends of autumn temperature and GSL ₂ suggested	
3	that regional warming in autumn was responsible for the may likely be the main cause for delays	
4	of in EOS and the extension of GSL occurred that we measured in the U.S. Great Basin during	
5	1982–2011 (Table 3 and Fig. 7d and 7f). The significant positive relationship we detected	
6	between the trends of GSL and mean $\frac{1}{D}NDVI$ in SSA indicated that the extension of GSL	
7	resulting from the delay of EOS was mainly responsible for the long term 30-year upward trend	
8	in mean vegetation greenness we observed in Great Basin during 1982-2011 (Fig. 9b).	
9	Changes Interannual variability in precipitation also appears to played a strong, and likely	
10	more important, role in controlling the interannual variability of <u>SSA[?]</u> vegetation greenness (on	
11	an annual basis (the calculated AIC values are smaller for precipitation and largerthan for	
12	temperature; Fig. 6). On a seasonal basis, the calculated AIC values (Table 1) still suggested that	
13	precipitation in winter, spring, and summer can better explain the interannual variability-of	
14	seasonal mean vegetation greenness in spring, summer, and autumn vegetation greenness. These	
15	results suggest that the underlying reason for this is that water availability strongly constrains	
16	biotic activity in dryland ecosystems, including plant seed germination, growth, and reproduction,	
17	the emergence of leaf-out, and GSL (e.g., Hadley and Szarek, 1981; Bradley and Mustard, 2005).	
18	Because perennial plants in dryland ecosystems often have are mostly deeply rootsed, increases	Formatted: Strikethrough
19	in pre-season precipitation, therefore, are likely to that increase soil water content in deep soil	
20	layers through soil infiltration, and thusare therefore likely to benefit vegetation growth in	
21	nextduring the following growing season. The reRelative importance analyses further indicated	
22	that the interannual variability of mean greenness in SSA was largely affected modulated by the	
23	variation of precipitation instead of temperature (Table 3), and the interannual variability of	

1	seasonal greenness in spring, summer, and autumn was attributableed mainly to the variation of
2	in precipitation (especially winter precipitation) in these seasons, rather than to temperature
3	variability (Tables 3).
4	4.5 Non-climatic factors that may influence vegetation phenology in the Great Basin
5	Although other factors – such as changes in biological soil crust (Ustin et al., 2009), shifts in
6	land covers at landscape-scales, and invasion of exotic species (e.g., <u>c</u> eheatgrass; Bradley and
7	Mustard, 2008) – <u>clearly</u> can affect vegetation phenology in the <u>Great Basin</u> dryland ecosystems
8	studied here, we lack of precise information about the spatio-temporal distribution of these
9	factors in the our study region. These other determinants of vegetation phenology also require
10	investigation and research funding, especially as they interact with climate variability and
11	climate change to affect ecosystem function and the services that these ecosystems provide.
12	Therefore, additional study research is necessary to examine how these factors, especially the
13	invasion and expansion of invasive species, may have already affected the temporal dynamics
14	and climatic sensitivity of vegetation phenology we observed in this study. In addition, the Also,
15	although we are confident in our calculation of SOS and EOS, interpolation of time-series bi-
16	weekly NDVI data to daily values may also affect further enhance the accuracy of SOS and EOS
17	estimates. Finally, although because our analysis excluded quantitation of NDVI during winter,
18	and and althoughbecause snowfall and snow covering may still occur sometimes in early spring
19	or in late fall in parts of the Great Basin, itprimarily occurs often accumulates only at in-high
20	elevational areas, effects of snow cover on . As a result, the effects of snow on NDVI values in
21	our study of low elevation sites were minimal because we focused on vegetation phenology in
22	low elevational areas. For example, in the southern and southeastern Great Basin (Fig. 4) where
23	snow rarely occurs in spring and autumn, there wereas a large amounts-number of points

1	showing a significant positive trend in vegetation greenness during 1982–2011. Theise can
2	justifyies factors allowed us to the robustlyness achieve our objectives of our results given to
3	quantify the effects the overall of continued -climate change, particularly acceleration of the long-
4	term warming trend taking place across the Great Basin in the last few decades (Tang and
5	Arnone, 2013).
6	5 Summary
7	Based on GIMMS NDVI data and from a regional perspective, our results suggested that
8	changes in total precipitation rather than mean surface air temperature in SSA was the major
9	factor controlling the interannual variability of mean vegetation greenness in dryland ecosystems
10	of the U.S. Great Basin. On a seasonal basis, pre-season precipitation in winter and spring
11	contributed more to the interannual variability of seasonal mean greenness in spring, summer,
12	and autumn. Nevertheless, climate warming although not significant in autumn was mainly
13	responsible for the extension of GSL resulting from delayed EOS, which in turn resulted in the
14	30-year positive trend in mean vegetation greenness in the dryland ecosystems. Overall, our
15	results suggest that both precipitation and temperature played an important but different role in
16	affecting vegetation phenology in the dryland ecosystems in the U.S. Great Basin. These changes
17	in phenology can potentially affect C fluxes in these semi-arid systems which can potentially may
18	contribute to modulating global CO ₂ fluxes. In addition, local changes in phenology can impact
19	other ecosystem service including grazing, providing wildlife habitat as well as altering fire
20	cycles (not sure if you want to go there).
21	Acknowledgements
22	This project benefited from the NSF EPSCoR grant for Nevada (NSF Cooperative Agreement
23	EPS-0814372). The NDVI data used in this study were downloadable from

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1	http://ecocast.arc.nasa.gov/data/pub/gimms/ and historical weather records were from the U.S.
2	West Regional Climate Center Data Archive. We greatly appreciate two-several anonymous
3	reviewers for their constructive comments that have helped improve this manuscript.
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1 Tables

2 **Table 1** Linear regression rRelationship of vegetation greenness to seasonal mean temperature

3 (SMT), total precipitation (STP), and pre-growing season precipitation (PSP); and AIC values.

Seasons	SMT		STP		PSP		\mathbf{AIC}^{\dagger}		
-	Slope	p<	Slope	p<	Slope	p<	SMT	STP or PSP	PSP
Spring	0.002	0.30	1.1e-4	0.15	1.1e-4	0.18	-162	-167 _s	-163 _w
Summer	-0.010	0.01	1.2e-4	0.16	3.4e-4	0.001	-154	-164 _s	-154 _w
Autumn	0.003	0.29	-5.6e-5	0.23	8.3e-6	0.86	-188	-189 _a	-190 _w

4 AIC[†] refers to the Akaike Information Criterion. The smaller the magnitude of the AIC value is, the better a

5 univariate linear regression model fits. The subscripts "w", "s", "a" represent winter, spring, and autumn,

6 respectively.

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7

8 Table 2 Linear regression rRelationships of SOS, EOS and GSL to temperatures (T)

Indices	Spring T		Autu	mn T	\mathbf{AMT}^{\dagger}		
	Slope	p<	Slope	p<	Slope	p<	
SOS	-2.7	0.001			-5.0	0.01	
EOS			0.7	0.43	0.2	0.87	
GSL	1.8	0.10	0.6	0.68	5.2	0.02	
		t the second					_

-- excluded for relationship analysis; AMT[†] -- annual mean temperature.

9 10

11 12

Table 3 The relative importance of annual/seasonal mean temperature (T) and precipitation (P)

14 to the variation of annual/seasonal mean NDVI based on multivariate regression analyses

Best multivariate regression model [†]	Stat	istics	LMG [†] for Regressors (R) [‡]			
	\mathbb{R}^2	p<	$R_1(\%)$	$R_2(\%)$	R ₃ (%)	R ₄ (%)
$SSA_N = SSA_T + SSA_P + SSA_T \times ANN_P$	0.22	0.09	8	75	17	
$MAM_N = MAM_T + DJF_P + MAM_p$	0.31	0.02	42	19	39	
$JJA_N = JJA_T + DJF_P + MAM_P + JJA_T \times DJF_P$	0.59	0.001	25	29	31	15
$SON_N = DJF_P + SON_P + SSA_T$	0.23	0.07	63	20	17	

15 [†]These models were selected based on adjusted-R square and p-values. The subscripts "N", "T", and "P" in each

16 model represent NDVI, temperature, and precipitation, respectively. "SSA", "MAM", "JJA" and "SON" represents

17 the period of March to November, spring, summer and autumn, respectively. LMG[†] refers to the averaging over

18 orderings of importance proposed by Lindeman, Merenda and Gold (LMG; Grömping, 2006). [‡] The order of

19 regressors corresponds to the order of those variables listed in multivariate regression model.

1 Figures







4 stations used in this study. (b) The distribution of NDVI points considered in this study.



Figure 2. The trends (dashed gray line) and variations (solid black line) of (a) mean vegetation
greenness (, (b) mean surface air temperature, and (c) total precipitation in the period of March to
November in the Great Basin during 1982–2011. Data shown in (a), (b), and (c) are anomalies
relative to their long-term (1982–2011) means, respectively.



1

2 Figure 3. The trends (dashed gray line) and variations (solid black line) of (a)~(c) seasonal

3 mean vegetation greenness, (d)~(f) seasonal mean temperature, and (g)~(i) seasonal total

4 precipitation in the Great Basin during 1982–2011. Data shown here are anomalies relative to

- 5 their <u>respective</u> long-term (1982–2011) seasonal means, respectively.
- 6



1 **Figure 4.** The spatial patterns of statistically significant (p<0.05) temporal trends in mean

2 vegetation greenness in (a) SSA (the period of March to November), (b) spring, (c) summer, and

3 (d) autumn during 1982–2011 in the Great Basin. The percentages were calculated against the

4 total of points considered in this study.





7 Figure 5. The trends (dashed gray line) and variations (solid black line) in (a) the start of

8 growing season (SOS), (b) the end of growing season (EOS), and (c) the growing season length

9 (GSL) in the Great Basin during 1982–2011.

10









seasonal mean temperature, and (f) the long-term trends in GSL and seasonal mean temperature
in <u>a</u>Autumn during 1982–2011. Data shown in (a), (c), and (e) are anomalies relative to their
<u>respective</u> 30-year means. <u>Data shown and-in</u> (b), (d), and (f) are derived trends (a loess curve
was used to derive the long-term trend of a variable against years) [with a best-fit linear
regression line shown in each graph panel ?].



7

Figure 8. The relationships (a) between mean vegetation greeness in summer and winter
precipitation, and (b) between mean vegetation greeness in autumn and winter precipitation
during 1982–2011. Data in (a) and (b) are anomalies relative to their long-term means,

11 respectively.

12



13

14Figure 9. The rRelationships (a) between mean annual surface air temperature in annual SSA

15 (the period of March to November) and the grown season length (GSL), and (b) between GSL

and mean vegetation greeness in SSA during 1982–2011.