Reviewer #1

General Comment: This paper compares surface air temperatures over China from observations and many atmospheric analyses, and seeks to improve understanding of biases in terms of deficiencies in the representation of forcing factors in the assimilating models used by the analyses. It shows that the effects of homogenising the observations are small compared with the differences between the analyses and the observations. It merits publication, but requires improvement to the presentation and discussion of results.

Response: Thanks for your high recommendation of our submission. Following your and Comment#2 constructive suggestions, the revised manuscript has been sent out for Professional English editing and we have carefully checked the revised paper and made the logic of Abstract concise and the logic of the revised paper smooth. Especially, we re-edited the Sections Discussion and Conclusions to make them clearer. We re-plotted new Fig. 3 to be more readable for readers. Below please find our point to point response to your comments.

Specific Comments:

1)

Comment: The language is generally clear, but needs a little sub-editorial refinement.

Response: Thanks, the manuscript has been sent out for Professional English editing and we have carefully made some language editing in the revised paper.

2)

Comment: Page 3, lines 44 to 50. ERA-20CM uses a newer version of the ECMWF model and sea-surface temperature analyses that are more homogeneous over time than ERA-Interim. The comparability of its pattern of trend biases with that of ERA-Interim cannot solely or necessarily be ascribed to its use of an ensemble technique. Note also that ERA-20CM used perturbed sea-surface temperature analyses, and did not include perturbations of the prescribed CMIP5 forcing. As such, classifying its approach as a “perturbed physical ensemble technique” does not seem appropriate.

Response: Thanks for your providing such information.

ERA-20CM includes the same forcing as CMIP5, please see Table 1 and website https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-20cm-model-integrations.

We revised it in the Abstract: The use of the ensemble technique adopted in the twentieth-century atmospheric model ensemble ERA-20CM significantly narrows the uncertainties associated with regional warming in reanalyses (standard deviation=0.15 ℃/decade).

The detailed evidence was added in the Section Discussion: Although it does not incorporate surface air temperature observations, ERA-20CM presents a pattern (with a mean of -0.04 ℃/decade and a standard deviation of 0.15 ℃/decade; Figs. 5 and 8) that is comparable to those of ERA-Interim and JRA-55 and **better than that of ERA-20C (mean of -0.08 ℃/decade and standard deviation of 0.20 ℃/decade; Figs. 5 and 8), which uses the same forecast model as ERA-20CM.** These results imply that ensemble forecasting could be used to meet important goals. **The ensemble forecasting technique used in ERA-20CM also displays advantages in that** it yields an improved simulated pattern of biases in the trends in R_s (SD=1.84 Wm^{-2}/decade, 171%), precipitation frequency (SD=2.78days/decade, 122%) and L_d (SD=1.25 W m^{-2}/decade, 82%) (Fig. 8).

3)

Comment: Page 4, line 58. Satellites should be included in the list.

Response: Added as suggested: …from a variety of sources, such as surface stations, ships, buoys, radiosondes, airplanes **and satellites.**

4)

Comment: Page 4, line 66. The models used to produce reanalyses do more than fill gaps in observations.

They are important for the quality control and bias adjustment of observations, which is especially important when merging the information provided by many different types of observation.

Response: Thanks for your providing such information, which was added in the lines **96-104** of the revised paper: These reanalyses produce global gridded datasets that cover multiple time scales and include a large variety of atmospheric, oceanic and land surface parameters, many of which are not easily or routinely observed but are dynamically constrained by large numbers of observations from multiple sources assimilated using fixed NWP models. During the data assimilation, prior information on uncertainties in the observations and models are used **to perform quality checks, to derive bias adjustments and to assign proportional weights. Therefore, such reanalyses add value to the instrumental record through their inclusion of bias adjustments, their broadened spatiotemporal coverage and their increased dynamical integrity or consistency.**

5)

Comment: Page 5, lines 83 to 92. MERRA-2 should be included in this list.

Response: Added as suggested: …and the National Aeronautics and Space Administration, the Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al., 2011) **and its updated version, MERRA-2 (Reichle et al., 2017).**

6)

Comment: Page 8, line 150, and in later places, including the labelling of figures. It is wrong to label the century-scale analyses that assimilate only surface pressure (and perhaps surface wind) observations as "climate quality" compared with the shorter "NWP" reanalyses that assimilate comprehensive sets of observations. Climate quality is something that has to be demonstrated, and is not just a matter of the type of reanalysis that is carried out. The ERA-Interim and JRA-55 "NWP" reanalyses give the best climate trends for surface air temperature, as the paper shows over China. The century-scale reanalyses still suffer from changes in observations over time, as the number of surface pressure and wind observations has increased enormously over the past one hundred or more years. Also, these reanalyses use sea surface temperature and sea ice analyses that depend on observations that have changed over time. Moreover, their avoidance of upper-air observations means that their climatological states are more subject to model biases than in "NWP" analyses in which observations help determine these states. The term "climate quality" should not be used to categorize some of the reanalyses for which results are presented.

Response: Thanks for your comments. Following the BAMS paper of Dee et al., (2014), we labeled them as '**NWP-like reanalysis**' and '**Climate reanalysis**' in the revised paper and all the figures.

Reference: Dee, D. P., M. Balmaseda, G. Balsamo, R. Engelen, A. J. Simmons, and J. N. Thépaut, 2014: Toward a consistent reanalysis of the climate system. *Bull. Am. Meteorol. Soc.*, 95, 1235-1248.

7)

Comment: Page 10, lines 184 to 192. It would be helpful for the reader to be informed how many of the 2200 or so stations provide data that are exchanged globally under the auspices of WMO. ERA-Interim and JRA-55 analyse surface air temperature data from those stations for which data are transmitted internationally, and perhaps some additional data to which they have access for early years, but data from a significant fraction of the 2200 or so stations were probably not used by these reanalyses. It would also be helpful to know whether the observational data used in this study are publicly available to anyone who might wish to carry out such a study, or for use in future reanalyses.

Response: Data at approximately 2400 stations are conditionally exchanged with the China Meteorological Administration, publicly unavailable. Since 1961, only 194 out of approximately 2400 stations are for global exchange (please see: http://data.cma.cn/en/?r=data/detail&dataCode=SURF_CLI_CHN_MUL_DAY_CES_V3.0). This information was added in the line **196**.

Note also that 824 out of approximately 2400 stations should be downloaded for the China Meteorological Administration for certain usage (http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html, in Chinese).

8)

Comment: Page 11, line 213 and pages 47 and 48. Table 1 needs some correction and tidying up. ERA-20CM did not use a 4D-VAR assimilation system as it was an ensemble of model runs. It used prescribed sea surface temperature and sea-ice analyses, but they were not produced by 4D-VAR. One column is headed "Related assimilated surface observations", but the entry for ERA-Interim includes reference to upper-air observations, and that for MERRA-2 includes reference to aerosol observations that are not surface ones. It is stated that ERA-Interim assimilated "land surface temperature" data. It did not. It did analyse "surface air temperature data over land", which is not the same variable. As discussed below in comment (10) it is probably better to refer to these data as analysed not assimilated.

Response: Thanks for your providing such information. We revised the main text and tidied up Table 1.

In Table 1, we corrected the column head 'Related Assimilated Surface Observations' as '**Related Assimilated and Analysed Observations**', 'land surface temperature' as '**near-surface air temperature**' in ERA-Interim, '4D-VAR' as '**3D-VAR**' in ERA-20CM and so on. For most surface observations in reanalysis, we used '**analysed**' instead of 'assimilated' where appropriate in the revised paper.

9)

Comment: Page 11, line 222. Surface pressure observations are not distributed homogeneously in space or (especially) time. Also, sea surface temperature and sea ice analyses are not of homogeneous quality, due to observational changes. See also comment (6).

Response: Thanks for your suggestion. We corrected it as 'relatively effective'.

10)

Comment: Pages 12 and 13, lines 246 to 251. The explanation of what ERA-Interim and JRA-55 do could be clearer. A background surface air temperature, at a height of two metres, is produced using a processing of the model-level background forecast with the help of Monin-Obukhov similarity profiles. The observations of surface air temperature are then analysed using a relatively simple analysis scheme. It is best not to use the word assimilated as the two-metre temperatures do not affect the starting atmospheric state for the next background forecast. But they are not simply postprocessed products either – in contrast to the products from other reanalyses. Some information is retained (assimilated) in that where appropriate the increments in surface temperature and corresponding ones in relative humidity are used to update soil temperature and humidity, and these do carry over into the next background forecast. It is nevertheless probably better to refer to the observations as analysed rather than assimilated.

Response: Thanks for your providing valuable information, which was added in lines **260-264**: However, the T_a in ERA-Interim and JRA-55 are post-processing products **by a relatively simple analysis scheme** between the lowest model level and the surface and are **analysed** using ground-based observations of T_a, with the help of Monin-Obukhov similarity profiles…

11)

Comment: Page 18, line 375. The better performance of ERA-Interim and JRA-55 is described as "mainly due to the post-processing of assimilated surface air temperature". If this statement is retained is should read "mainly due to their analysis of surface air temperature data", as discussed in comment (10). The statement is probably correct, but do the authors have evidence that this is the case? Perhaps ERA-Interim and JRA-55 simply have a better background forecast of surface air temperature due to other aspects of their data assimilation system. If the statement is to be retained, it needs to be backed up by showing that the background forecast surface air temperatures from ERA-Interim and JRA-55 are not significantly better than the surface air temperatures from the other reanalyses. In that case, analysing the surface air temperature observations must be the main reason they provide a better product.

Response: Corrected in the revised paper as suggested: **perhaps due to their analysis of surface air temperature observations** in ERA-Interim and JRA-55 (Table 1).

12)

Comment: Page 19, lines 383-385. It should be noted that CERA-20C used a newer model cycle than ERA-20C, and some problems that were found to affect ERA-20C were fixed in CERA-20C. So CERA-20C's better performance than ERA-20C cannot be ascribed entirely to the use of a coupled forecast model and data assimilation.

Response: Thanks for your information, and we added such information in the revised paper: **perhaps related to** the inclusion of coupled climate forecast models and data assimilation, as well as the assimilation of surface pressure data in CERA-20C (Fig. 3 and Table 1).

13)

Comment: Page 19, line 389. The type of analysis presented in section 3.3 needs to be interpreted carefully when it comes to ERA-Interim and JRA-55. This is because their surface air temperature products involve analyses of surface air temperature observations, and values depend on the analysis increments to the background as well as to contributions via the background forecasts from key physical factors that influence surface air temperature. For example, the sentence in lines 475 to 477 on page 23 reads as if the trend biases in surface air temperature have contributions from biases in various physical forcings. But in ERA-Interim and JRA-55 such biases in physical forcing will tend to be counterbalanced by the changes the observations bring to the background forecasts. The balancing will not be perfect, so ERA-Interim and JRA-55 may inherit some of the deficiencies in forcing, but these deficiencies are likely to be much weaker than would be the case if surface air temperature observations had not been analysed.

Response: Thanks for your information, and we added such information in the end of **Section 3.4**: Note also that the incorporation of the observed changes in surface air temperatures in ERA-Interim and JRA-55 may introduce biases into the trends in the output T_a values; however, the use of partial correlation and regression analysis would lead to smaller impacts of the biases in these physical variables in quantifying their contributions to the trends in T_a.

14)

Comment: Pages 21 and 22, lines 443 to 445. Again (see comment (11)) it is asserted that the better performance of ERA-Interim and JRA-55 is due to the assimilation [analysis] of surface air temperature [observations]. This is almost certainly part of the story, but unlikely to be the only reason these two reanalyses perform better than the others. A phrase such as “in part, at least,” is needed after the word “due”.

Response: Corrected as suggested.

15)

Comment: Page 28, line 28. It is stated that ”only vegetation is included as climatology”. This is wrongly worded. Perhaps the authors mean “vegetation is only included as [a] climatology”. A number of fields other than vegetation are specified climatologically.

Response: Corrected as suggested in the lines **623-625**: In the reanalyses, vegetation is **only included as climatological information**, but the vegetation displays a growth trend during the study period of 1979-2010 within China (Fig. S23).

16)

Comment: Page 29, lines 607 to 614. I simply do not understand this paragraph.

Response: We revised this paragraph: We consider the degree to which the ensemble assimilation technique can improve the spatial patterns of the biases in the trends in Ta in the reanalyses. We find that this technique can detect the biases in the trends in Ta **over more another approximately 12% (8%)** of the grid cells in CERA-20C, which incorporates 10 ensemble members (NOAA 20CR2vc and NOAA 20CR2v employ 56 ensemble members) (Figs. 5 l-n). However, the biases in the trends in Ta over these grid cells are not significant at a significance level of 0.05, according to Student's t-test, implying that the ensemble assimilation technique cannot explain the spatial pattern of the biases in the trends in Ta identified in this study (in Figs. 5 l-n).

17)

Comment: Pages 29 to 30, lines 615 to 626. It is misleading to label the models used for the century-scale reanalyses "climate models" and the models used for shorter reanalyses "NWP models". The same ECMWF models are used for the two types of reanalysis, apart from a tendency for more recent reanalyses to use newer model versions.

Response: Thanks for your comments. Following the BAMS paper of Dee et al., (2014), we labeled them as '**NWP-like reanalysis**' and '**Climate reanalysis**' in the revised paper and all the figures.

Reference:

Dee, D. P., M. Balmaseda, G. Balsamo, R. Engelen, A. J. Simmons, and J. N. Thépaut, 2014: Toward a consistent reanalysis of the climate system. *Bull. Am. Meteorol. Soc.*, 95, 1235-1248.

18)

Comment: Page 30, lines 629. The reference to ERA-20CM is incorrect, as its circulation is not controlled by pressure data. No meteorological observations are assimilated in ERA-20CM.

Response: Thanks for your good comment and we corrected it in lines **675-677**: In ERA-20CM, the atmospheric circulation patterns are influenced by SSTs and sea ice and then partly mediate the influence of global forcings on the trends in T_a.

19)

Comment: Page 32, line 682. High temporal resolution in situ and satellite observations of precipitation are available only for recent years, so their use in reanalysis to refine trend estimates will be limited until longer time series of observations have been accumulated.

Response: Thanks for your comment. We delete this part.

20)

Comment: Page 33, lines 690 to 692. See comment (2) regarding the nature of the perturbations applied in ERA-20CM.

Response: Thank you very much. Please see Comment #2.

21)

Comment: Page 33, line 704. It is not clear why the Argo system is mentioned here, as it is not primarily an observing system for SST and sea ice, and data have been available in substantial numbers for little over a decade, posing a problem for homogeneity.

Response: Thanks for your comment. We delete it.

Reviewer #2

General Comment: The study attempts to assess the value of various global reanalysis products over the Chinese domain by comparison to a homogenized set of station data. The overall approach is logical. The findings with regards to which reanalyses products are high quality are in line with existing understanding. Some effort to understand the potential thermodynamic and boundary condition causes of differences are interesting and novel although could be presented much more simply. It is clear that a huge amount of effort has been undertaken to access and analyse a wealth of data. As such, the authors are to be commended on a substantive body of work. However, I have some concerns around aspects of the analysis and presentation. The work may be publishable in ACP following revisions if they satisfactorily address my concerns.

Response: Thanks for your effort to evaluate our submission and high recommendation. Below please find our point to point response to your comments.

Specific Comments:

1)

Comment: Treatment of observations

The main issue with the analysis is the treatment of a single homogenized series of temperature observations as constituting a 'truth' against which it is possible to make definitive resulting assessments of the reanalyses products. In reality no single approach to homogenization of observations can ever yield a perfect reconstruction of the true evolution of the observed variable. Therefore the observations even after homogenization cannot be treated as a demonstrable truth against which definitive statements of reanalysis quality can be made. In cases where offsets between the observations and reanalysis are substantive it is relatively simple to diagnose that there must be an issue in the given reanalysis product as, although imperfect, the uncertainty in the observations can be reasonably bounded. However, many of the differences between candidate reanalysis products and the homogenized reanalyses instead fall into the grey zone whereby the difference is smaller than, or of comparable magnitude to, the potential residual uncertainty in the homogenized series.

The authors could address this point by collecting the substantive family of homogenized temperature station series that have been created over China over the past decade or so and comparing the full family of homogenized series to the full family of reanalyses products. This would serve to substantially strengthen their overall analysis under the assumption that the family of homogenized products and the family of reanalysis products both consist of random draws from the parent distributions of possible homogenized / reanalyzed series. Without undertaking such a step, although the work may just about be publishable, its utility will be substantively compromised.

Similarly, the observations of the studied covariates (cloudiness, rainfall, radiation etc.) must be uncertain. Again, when differences are substantive inferences can be made without issue. It is when distinctions between the reanalyzed and observed fields are small that interpretation becomes difficult. In such cases the remaining uncertainties in the observations of the covariates limits what inferences can be made.

Response: Thanks for your comments.

Yes, you are right. Single homogenized series is impossibly perfect. In the revised paper, the Student's *t*-test was conducted to difference between reanalysis and homogenized series for considering both uncertainties at the significance level of 0.05. This information was added in the lines **313-315**.

We are keeping cooperating with several Chinese groups, each of which conducts temperature data using different homogeneous methods. These dataset can not be used simultaneously in this study, because they are not of the same time period and identical station, and do not include homogeneous datasets of studied covariates (cloudiness, precipitation frequency, radiation etc.) in this study.

Furthermore, only using the homogeneous time series (not including adjusted time series) at the significance level of 0.05, it can show almost the same results as those from all the time series in the revised paper (see **Fig. 5**).

2)

Comment: Clarity of analysis

In many places the text is hard to follow. This mainly arises through choices as to how to structure the sections and individual paragraphs and this makes it hard as a reader to follow the logical arguments being made by the authors.

The abstract, in particular, is hard to follow as submitted. Efforts at restructuring to make more clearly the arguments the authors wish to put forwards would increase the value of the piece.

The methods section isn't entirely clear and in some places it is questionable whether sufficient detail is given to allow replicability. In particular the set of seven equations is given without sufficiently clear justification and without detail as to whether these are applied gridpoint-wise, smoothed etc.

In the results, the continual listing of regions and reanalyses in different contexts is confusing and hard for a reader to unpick. Greater use of figures and / or tables may serve to improve the messaging aspects here. I find myself trying to connect 12 sets of dots to get a feeling how each reanalysis performs in each aspect in each region and then compare all the joined dots in my head but the problem gets way too big to do so very quickly. The authors have done a huge amount of analysis but the choice of primarily describing in text without tabular and / or visual ways of summarizing the interconnectedness arguments being made is an impediment to reader understanding.

I find the results, discussion and conclusion sections to be substantively overlapping. These sections would benefit from substantive redrafting and reordering. The results should outline what is found. The discussion should highlight the principal findings and implications. The conclusion should be at most 2-3 paragraphs of key take away messages. Presently the results and discussion feel repetitive and the current conclusions feel to me more like a discussion.

Finally, the text would benefit from substantial input from a native English speaker if available. I am always in two minds over such a comment because I am acutely aware I could write to nothing like the standard in any other language. The authors therefore have my greatest respect for not only undertaking the science but writing it in a second language. But, equally, if the authors wish to have impact they would be served by careful input from a native speaker and it would be remiss of me not to suggest this.

Response: Thanks for your detailed comments. Following your constructive suggestions, we have carefully checked the revised paper and made the logic of Abstract concise and the logic of the revised paper smooth. Especially, we re-edited the Sections Discussion and Conclusions to make them non-overlapping.

We added more details in the **Section Method 2.4** to make it easier to follow: To further investigate the relationship between the spatial distributions of the biases in the trends in T_a and the relevant parameters among the twelve reanalysis products, the weighted total least squares (WTLS) is adopted, **in which the spatial standard deviations and correlations of pairs of variables on 1 °×1 ° grid cells were included** (Reed, 1989;York et al., 2004;Golub and Van Loan, 1980;Hyk and Stojek, 2013;Tellinghuisen, 2010).

In the Monte Carlo method, the grid index for the 1 °×1 ° grid cells over China, **which ranges from 1 to 691, is generated as a random number.** On this basis, we can sample the spatial pattern in the biases in the trends in T_a, R_s, L_d and precipitation frequency.

We re-plotted **the Fig. 3** to be clearer for reader, especially using different markers for both grouped reanalyses.

Again, following Comment #1 and your suggestions, we have sent out the revised paper for Professional English editing and we have carefully made some language editing in the revised paper.

3)

Comment: Figure suggestions

For the reader it is important that you explicitly define the regions. I would add a new Figure 1 consisting of a map of China in which the different regions are clearly demarcated. The regions are listed in the caption of Figure 1 but there is nothing I can see in Figure 1 which actually denotes this.

Almost all figures use a rainbox colour scale which is inaccessible to those who are colour-blind, which is a not inconsiderable proportion of the population. Numerous colour-blind friendly colour schema are available and consideration should be made as to their use to improve accessability.

I find many figures hard to understand. The authors are trying to pack a lot of information into these and in many cases because they are postage stamps this is hard to see and interpret. I find Figure 8 particularly difficult and, if I am honest, even after spending 10 minutes trying to understand it suspect that I do not. If you make the reader work this hard they will give up and move on. In general work on making the figures more intuitive and accessible would help enormously.

Response: Thanks for your constructive comments. Please see the region division in **the Fig. 1c** and its corresponding figure caption.

We have made much efforts to try but fail to adopt various colorbars for three variables (***RGB composite***) instead of rainbox colourbars. We also found quite a few literatures used the same rainbox colorbars to plot three variables, e.g., published in *Science* (Nemani et al., 2003) and *Nature* (Seddon et al., 2016).

We re-plotted **the Fig. 3** to be clearer for reader, especially using different markers for both grouped reanalyses. We re-wrote all the relevant figure captions including **the caption of Figure 8** to be concise for easy getting main information.

Reference:

Nemani R R, Keeling C D, Hashimoto H, et al. Climate-driven increases in global terrestrial net primary production from 1982 to 1999[J]. *Science*, 2003, 300(5625): 1560-1563.

Seddon A W R, Macias-Fauria M, Long P R, et al. Sensitivity of global terrestrial ecosystems to climate variability[J]. *Nature*, 2016, 531(7593): 229.

On the Suitability of Current Atmospheric Reanalyses for Regional Warming Studies over China

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Abstract

Reanalyses ~~have been~~are widely used because they add value to ~~the~~ routine observations by generating physically or ~~/~~dynamically consistent and spatiotemporally complete atmospheric fields. Existing studies ~~have extensively discussed~~include extensive discussions of the ~~their~~ temporal suitability of reanalyses ~~–~~ in ~~global change study~~studies of global change. This study ~~moves forward on~~adds to this existing work by investigating the ~~their~~ suitability of reanalyses in studies of ~~for~~ regional climate change, in which ~~study where~~ land-atmosphere interactions play a ~~more~~ comparatively important role. ~~Here~~In this study, surface air temperatures (T_a) from 12 current reanalysis products ~~were~~ are investigated~~, focusing on~~; in particular, the spatial patterns of ~~T_a trends~~trends in T_a are examined~~,~~ using homogenized measurements of T_a made~~from 1979 to 2010~~ at ~2200 meteorological stations in Chin~~a. Results~~a from 1979 to 2010. The results show that ~80% of the ~~T_a mean differences~~mean differences in T_a between the reanalyses and the ~~*in-situ*~~*in situ* observations ~~are~~ can be attributed to the differences in elevation between the stations and the ~~model-grid elevation~~model grids~~ differences, denoting good skill in~~. Thus, the T_a ~~climatology~~ climatologies display good skill, and these findings rebut~~ting the~~ ~~previously reported~~previous reports of ~~T_a biases~~biases in T_a. However, the ~~T_a trend biases~~biases in the T_a trends in ~~T_a in~~ the reanalyses ~~display spatial divergence~~diverge spatially (standard deviation=0.15-0.30 ℃/decade ~~at~~ using 1 °×1 ° ~~grids~~grid cells). The simulated ~~T_a trend biases~~biases in the trends in T_a correlate well with those of precipitation frequency, surface incident solar radiation (R_s), and atmospheric

downward longwave radiation (L_d) ~~among~~ ~~in~~among the reanalyses (r=-0.83, 0.80 and 0.77;~~,~~ p<0.1)~~ with~~ when the~~their~~ spatial patterns of these variables are considered. ~~Over southern China~~ T~~, t~~he ~~T_a trend biases~~biases in the trends in T_a over southern China ~~(by order of~~~~(which are~~ on the order of -0.07 ℃/decade) are caused by~~ the trend biases in R_s~~biases in the trends in R_s, L_d and ~~the frequency of precipitation~~precipitation frequency~~(by order of~~ on the order of 0.10 ℃/decade,~~), L_d (by order of~~ -0.08 ℃/decade, ~~) and precipitation frequency (by order of~~and -0.06 ℃/decade, respectively). ~~Over northern China~~ T~~, t~~he ~~T_a trend biases~~biases in the trends in T_a over northern China ~~(by order of~~~~(which are~~ on the order of -0.12 ℃/decade)~~ jointly~~ result jointly from those in L_d and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency. Therefore, improving the simulation of ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and R_s helps to maximize the ~~regional climate signal component~~signal component corresponding to regional climate. ~~Besides,~~ In addition, incorporating vegetation dynamics in reanalyses and the use of accurate aerosol information, as in the Modern-Era Retrospective Analysis for Research and Applications, version 2~~MERRA-2~~ (MERRA-2~~Modern-Era Retrospective Analysis for Research and Applications, version 2~~), would ~~would advance~~~~result in~~ lead to improvements in the ~~regional warming modeling~~modelling of regional warming. The use of the e~~E~~nsemble technique ~~(~~adopted in ~~ERA-20CM, a~~ the ~~twentieth century~~twentieth-century atmospheric model ensemble ERA-20CM ~~without~~ ~~, which does not include the assimilating~~ ~~assimilation of~~ ~~observations,)~~ significantly narrows the ~~regional warming~~

~~uncertainties~~uncertainties associated with regional warming in reanalyse~~i~~s (standard deviation=0.15 ℃/decade). ~~Besides, the T_a trend biases show negative spatial correlations (approximately r=-0.26, p=0.00) with inverted trend in NDVI (Normalized Difference Vegetation Index) implying that incorporating vegetation dynamics can advance regional warming modeling. Inclusion of accurate aerosol information in MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications, version 2) helps improve regional climate simulation. ERA-20CM (a twentieth century atmospheric model ensemble without assimilating observations) presents a comparable pattern of the T_a trend biases (standard deviation=0.15 ℃/decade) to ERA-Interim and JRA-55 (the Japanese 55-year Reanalysis) that assimilating some T_a observations, which indicates perturbed physical ensemble technique significantly narrows regional warming uncertainties in reanalyses.~~

1. Introduction

Observations and models are two fundamental approaches ~~to~~ used in the understanding of climate change. ~~The o~~Observations ~~directly~~ provide a direct link ~~with~~ to the climate system via ~~measuring~~ instruments, whereas ~~and~~ models ~~has~~ provide an indirect link ~~by involving~~and include information ~~received~~ derived from measurements, prior knowledge and theory.~~–~~

A large number of meteorological observations have been accumulated~~, including~~. These measurements, which are derived from a variety of sources, such as surface stations, ships, buoys, radiosondes, airplanes and satellites, record quantities that include near-surface and upper-air temperatures, humidity, wind and pressure ~~from a variety of sources-surface stations, ships, buoys, radiosondes, airplanes and satellites~~. They constitute a major source of atmospheric information through the depth of the troposphere but suffer from incomplete spatiotemporal coverage and ~~observed error~~observation errors, including systematic, random and ~~representative~~ representation errors. Recent satellite-based observations have much better coverage ~~but~~; however, they suffer from other notable limitations, including ~~notably~~ temporal inhomogeneities~~y~~ (e.g., satellite drift) and retrieval errors (Bengtsson et al., 2007). These ~~space-time~~ spatiotemporally varying gaps restrict the effective application of observations alone ~~to be effectively applied~~ in climate research.

To fill in the gaps in ~~the~~ observations, ~~a~~ models ~~is~~ are needed. ~~The~~ Such models ~~can~~ can be very simple~~, e.g.,~~; examples of simple models include linear interpolation or geo-statistical approaches that are based on the spatial and temporal autocorrelation of the observations. However, these models lack the necessary dynamical or ~~/~~physical mechanisms. ~~With~~ Given the steady progress ~~in the~~of numerical weather prediction (NWP) models in ~~charactering~~characterizing the ~~the~~ global atmospheric circulation in the early 1980s (Bauer et al., 2015), ~~an original~~the first generation of ~~‘~~reanalyse~~i~~s~~’~~ ~~was~~was ~~achieve~~produced~~d~~ by combining observations and dynamic models to provide the first global atmospheric datasets ~~available~~ for use in scientific research (Bengtsson et al., 1982a, b).

After realizing the great value of this kind of reanalysis ~~for~~ in atmospheric research, a step forward ~~was~~was taken with the suggestion made by Bengtsson and Shukla (1988) and Trenberth and Olson (1988) that most meteorological observations should be optimally assimilated under a fixed dynamical system over a period of time long enough to be useful for climate studies. In this way, available observations are ingested by advanced data ~~-~~assimilation techniques to provide a continuous initial state for an ~~the~~ NWP model to produce the next short-term forecast~~, t~~. This procedure thus ~~generating~~ generates physically consistent and spatiotemporally complete three-dimensional atmospheric fields that are updated in light of observations.

~~Under this~~Taking this suggestion as a guide, and given the improvements that have been made since the mid-1990s in the integrity of the observations, the models and the assimilation methods used, successive generations of atmospheric reanalyses established by several institutes have ~~improvements~~ improved in quality ~~with better observation integrity, better models and better assimilation methods since the~~

~~mid-1990s~~. These reanalyses include the first two generations of global reanalyses ~~from~~ produced by the National Centers for Environmental Prediction ~~[~~, NCEP-R1 (Kalnay et al., 1996) and NCEP-R2 (Kanamitsu et al., 2002)~~]~~ and the reanalyses produced by~~,~~ the European Centre for Medium-Range Weather Forecasts (ECMWF)~~[~~, ERA-15 (Gibson et al., 1997), ERA-40 (Uppala et al., 2005), and ERA-Interim (Dee et al., 2011b);~~],~~ the Japanese Meteorological Agency, ~~[~~JRA-25 (Onogi et al., 2007) and JRA-55 (Kobayashi et al., 2015);~~]~~ and the National Aeronautics and Space Administration ~~[~~, the Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al., 2011) and its updated version, MERRA-2 (Reichle et al., 2017)~~]~~.

These reanalyses produce global gridded datasets that cover multiple time ~~-~~scales~~d, global gridded datasets including~~ and include a large variety of atmospher~~ic~~e, ~~sea~~ oceanic and land surface parameters, many of which are not easily or routinely observed but are dynamically constrained by ~~a great number~~large numbers of ~~multiple sourced observations~~observations from multiple sources assimilated ~~under a~~using fixed NWP models. During the data assimilation, prior information ~~about~~ on uncertainties in the observations and models are used ~~for~~ to perform quality checks, to derive bias adjustments and to assign ~~their~~ proportional weights. Therefore, such reanalyses add value to the instrumental record ~~in the aspects of~~through their inclusion of bias adjustments, their broadened spatiotemporal coverage and their increased dynamical ~~integrality~~integrity or ~~/~~consistency.

Previous studies have revealed that such reanalyses have contributed significantly to a more detailed and comprehensive understanding of the dynamics of the Earth's atmosphere (Dee et al., 2011b~~;~~; Kalnay et al., 1996~~;~~; Nguyen et al., 2013~~;~~; Kidston et al., 2010~~;~~; Simmonds and Keay, 2000~~;~~; Simmons et al., 2010~~;~~; Mitas and Clement, 2006). Extensive assessment studies have reported that most reanalyses ~~have~~ display a certain level of performance in terms of their absolute values (Betts et al., 1996~~;~~; Zhou and Wang, 2016a~~;~~; Betts et al., 1998), interannual variability (Lin et al., 2014~~;~~; Lindsay et al., 2014~~;~~; Zhou and Wang, 2017a, 2016d~~;~~; Wang and Zeng, 2012), distributions (Gervais et al., 2014~~;~~; Heng et al., 2014~~;~~; Mao et al., 2010) and relationship ~~of inter-~~s among variables (Niznik and Lintner, 2013~~;~~; Cash et al., 2015~~;~~; Zhou et al., 2017~~;~~; Zhou and Wang, 2016a~~;~~; Betts, 2004) over regions worldwide. However, these aspects of reanalyses still contain~~there are still~~ certain errors ~~in these aspects~~ ~~so as to~~that restrict the~~ir~~ general use of reanalyses, especially ~~for~~ in climate applications.

The~~se~~ errors ~~emerging in~~displayed by reanalysis products ~~can be summarized into~~arise from three sources: observation error, model error and assimilation error (Thorne and Vose, 2010~~;~~; Parker, 2016~~;~~; Lahoz and Schneider, 2014~~;~~; Dee et al., 2014~~;~~; Zhou et al., 2017). ~~Specially,~~Specifically, ~~the~~ observation error incorporates systematic and ~~/~~random errors in instruments and ~~its~~ their replacements, errors in data reprocessing and ~~representative error~~representation error ~~in~~, which arises due to the spatiotemporal incompleteness of observations (Dee and Uppala, 2009~~;~~; Desroziers et al., 2005)~~; the m~~. Model error ~~mainly~~ refers mainly to the inadequate representation of physical processes in ~~the~~ NWP models (Peña and Toth, 2014~~;~~; Bengtsson et al., 2007),

~~e.g.,~~such as the lack of time-varying ~~setting of~~ surface conditions~~[~~, such as vegetation growth (Zhou and Wang, 2016a~~;~~; Trigo et al., 2015),~~]~~ and incomplete cloud-precipitation-radiation parameterizations (Fujiwara et al., 2017~~;~~; Dolinar et al., 2016)~~; the a~~. Assimilation error ~~involves~~describes ~~mapping~~ errors that arise in the mapping of the model space to the observation space and errors in the topologies~~y~~ of ~~the~~ cost functions (Dee, 2005~~;~~; Dee and Da Silva, 1998~~;~~; Lahoz and Schneider, 2014~~;~~; Parker, 2016).

These reanalyses mentioned above consist of the true climate signal and the ~~some~~ nonlinear interactions among the observation error, the model error, and the assimilation error that arise during the assimilation process. These time-varying errors can ~~thus~~ introduce ~~a fictitious~~spurious trends without being eliminated by ~~the~~ data assimilation systems. Many spurious variations in ~~the~~ climate signals ~~have~~ were ~~been~~ ~~also~~also ~~-~~identified in the ~~early-~~early-generation reanalyses (Bengtsson et al., 2004~~;~~; Andersson et al., 2005~~;~~; Chen et al., 2008~~;~~; Zhou and Wang, 2016d, 2017a~~;~~; Zhou et al., 2017~~;~~; Schoeberl et al., 2012~~;~~; Xu and Powell, 2011~~;~~; Hines et al., 2000~~;~~; Cornes and Jones, 2013). Therefore, ~~the~~ reanalyse~~i~~s produced ~~under~~ using ~~the guide of~~ the existing reanalysis strategy may not accurately capture ~~the~~ climate trends (Trenberth et al., 2008), even though they may contain ~~having a~~ relatively accurate estimates of synoptic or interannual variations ~~of~~ in the Earth's atmosphere.

An emerging requirement for climate applications of reanalysis data is the accurate representation of decadal variability, further increasing the confidence in the estimation~~e~~ of climate trends. This kind of climate reanalysis is required to be ~~to great~~

~~extent~~ free, to a great extent, from~~of~~ other spurious non-climatic signals introduced by changing observations, ~~imperfect model~~model imperfections and assimilation error~~,~~ ~~i.e., to keep the time consistency~~; that is, they must maintain temporal consistency. Therefore, the extent to which ~~the estimate of c~~climate trends ~~by climate~~can be assessed using reanalyse~~i~~s ~~can be realized attracts~~attracts much attention and sparks heated debates (Thorne and Vose, 2010~~;~~; Dee et al., 2011a~~;~~; Dee et al., 2014~~;~~; Bengtsson et al., 2007).

~~With~~ Given the great progress that has been made in climate forecasting models (which provide more accurate representations of climate change and variability) and coupled data assimilation,~~ a lot of~~ many efforts have~~s~~ been made by several institutes to build ~~the~~ consistent climate reanalyse~~i~~s ~~under the climate strategy that~~using the strategy of assimilating a relatively ~~few~~small number of~~ but~~ high-quality long-term observational datasets~~s~~. The climate reanalyses of this n~~N~~ew generation ~~of climate reanalyses~~ extend back to the late nineteenth century and ~~are~~include the Climate Forecast System Reanalysis (CFSR), which is~~ from~~ produced by the National Centers for Environmental Prediction~~ [CFSR~~ (Saha et al., 2010)~~]~~;~~,~~ NOAA 20CRv2c, which is produced by the University of Colorado's Cooperative Institute for Research in Environmental Sciences (CIRES)~~ together~~ in cooperation with the National Oceanic and Atmospheric Agency (NOAA)~~ [NOAA 20CRv2c~~ (Compo et al., 2011);~~]~~ and ~~[~~ERA-20C (Poli et al., 2016), ERA-20CM (Hersbach et al., 2015) and~~–~~ CERA-20C (Laloyaux et al., 2016), which are~~]~~ produced by the ECMWF~~ [ERA-20C (Poli et al., 2016), ERA-20CM (Hersbach et al., 2015) and CERA-20C (Laloyaux et al., 2016)]~~.

Compo et al. (2013) suggested that the NOAA 20CRv2c reanalysis can reproduce the trend in global mean surface air temperatures. In addition, the uncertainties estimated from multiple ensembles are provided to increase the confidence of the climate trends (Thorne and Vose, 2010~~,~~; Dee et al., 2014).

From~~ the~~ NWP-like reanalyse~~i~~s to climate reanalyse~~i~~s, existing ~~researches~~studies ~~mainly focus on~~focus mainly on comparing the differences in temporal variability between the reanalyses and observations~~,~~ using some statistical metrics, e.g., the mean values, standard deviations, interannual correlations, probability density functions and trends of surface air temperature over regions worldwide. These evaluations ~~actually~~ provide ~~an~~ insight into the temporal evolution of the Earth's atmosphere. However, ~~it lacks~~they lack the performance evaluations~~ of~~ used in reanalyse~~i~~s in representing the spatial patterns of these statistics associated with the role of the coupled land-atmosphere and dynamical processes of the climate system. Moreover, the assessment of these spatial patterns provides a direct ~~way to~~means of examining~~e~~ the most ~~distinguished~~ prominent advantage of reanalyse~~i~~s~~ that~~ over~~ the~~ geo-statistical interpolation~~ does not have, and thereby~~; thus, the ~~assessment of the~~ spatial patterns ~~remains to be~~require comprehensive~~ly~~ investigation~~ed~~.

~~Using~~ This study employs ~~the highly-dense~~high-density station-based datasets of quantities including surface air temperatures (T_a), the surface incident solar radiation (R_s), the surface downward longwave radiation (L_d), and precipitation measured~~from 1979 to 2010~~ at ~2200 meteorological stations within China from 1979 to 2010~~ over China, this study provides~~. It provides a quantitative examination of the simulated patterns of ~~T_a variations~~variations in T_a ~~from~~ in both the ~~the~~ NWP-like and~~to~~ climate reanalyses~~, including~~ and considers the ~~-~~climatology, the interannual variability, the mutual relationships~~ between~~ among relevant quantities, the long-term trends and their controlling factors. The results ~~identified~~ indicate the strengths and weaknesses of the current reanalyses when applied in~~in~~ regional climate change studies and provide possible ways to improve these reanalyses in the near future.

2. Data and Methods

2.1 ~~Observation Data~~Observational Datasets

The latest comprehensive daily dataset (which contains averages at 0, 6, 12, and 18 UTC) of quantities~~ including~~ that include T_a, precipitation, sunshine duration, relative humidity, water vapor pressure, surface pressure and the cloud fraction from approximately 2400 meteorological stations in China from 1961 to 2014, ~~out~~ of which only approximately 194 participate in~~for~~ global exchanges, ~~was~~is obtained from the China Meteorological Administration (CMA;~~,~~ http://data.cma.cn/data). Approximately 2200 stations with complete and homogeneous data ~~were~~are selected for use in this study (Wang and Feng, 2013~~;~~; Wang, 2008~~;~~; Wang et al., 2007). The h~~H~~igh density of meteorological stations in China ~~is beneficial to~~promotes the representation of~~ and assess the simulated skill of~~ regional patterns in surface warming by reanalyse~~i~~s and the assessment of the skill of simulations.

~~The~~ R_s values based on the revised Ångström-Prescott equation (Wang et al., 2015~~;~~; Yang et al., 2006~~;~~; Wang, 2014) ~~was~~ are used in this study. The derived R_s ~~has~~

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~~considered~~values consider the effects of Rayleigh scattering, water vapor absorption and ozone absorption (Wang et al., 2015~~;~~; Yang et al., 2006) and can accurately reflect the ~~impact~~ effects of aerosols and clouds on R_s over China (Wang et al., 2012~~;~~; Tang et al., 2011). Several intensive studies have reported that the derived R_s values can accurately depict the interannual, decadal and long-term ~~variances of~~variations in R_s (Wang et al., 2015~~;~~; Wang, 2014~~;~~; Wang et al., 2012).

~~The~~ L_d is typically estimated by first determining the clear-sky radiation and atmospheric emissivity (Brunt, 1932~~;~~; Choi et al., 2008~~;~~; Bilbao and De Miguel, 2007), and then correcting for the cloud fraction (Wang and Liang, 2009~~;~~; Wang and Dickinson, 2013). The derived L_d values can directly reflect the greenhouse effect of ~~atmosphere water~~atmospheric water vapor and clouds. Additionally, a precipitation event ~~was~~ is defined as daily ~~one day with~~ precipitation of at least 0.1 mm ~~daily~~ in this study, which ~~was~~ has been shown ~~as~~ to provide a good ~~indicator in reflecting~~indication of the effects of precipitation ~~impact~~ on the interannual variability and trends ~~of~~ in T_a (Zhou et al., 2017). ~~In all,~~Taken together, the derived R_s and L_d values are able to physically quantify the effects of solar radiati~~ve effect~~on and the greenhouse effect on surface warming. ~~Precipitation frequency~~~~The frequency of precipitation~~Precipitation frequency can regulate the partitioning of available energy into latent and sensible heat fluxes~~,~~ and ~~then~~ thus modulates the ~~variance of~~variations in T_a (Zhou et al., 2017~~;~~; Zhou and Wang, 2017a).

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2.2 Reanalysis Products

~~All the~~All of the major global atmospheric reanalysis products ~~were~~ are included in this study (Table 1). The reanalyses ~~were~~ are summarized below ~~from~~ in terms of three aspects, i.e., the observations assimilated~~,~~ and the forecast model and ~~assimilated method~~assimilation method used. The NWP-like reanalyses assimilate~~d~~ many ~~of multi-sourced~~ conventional and satellite datasets from multiple sources (Table 1)~~, whose spatiotemporal errors vary with time,~~ to characterize the basic upper-air atmospheric fields; the spatiotemporal errors of these datasets vary with time. In particular, the ERA-Interim and JRA-55 reanalyses incorporate some observations of T_a~~,~~ and the MERRA2 reanalysis includes aerosol optical depth estimates from satellite retrievals and model simulations based on emission inventories~~y~~, whereas most of the other reanalyses~~s~~ use ~~the~~ climatological aerosols (Table 1). To derive ~~long-term~~ consistent long-term climate signals, the new strategy ~~that~~ adopted by climate reanalyses ~~adopt is to~~involves the assimilation of a small number of~~e few but~~ relatively effective ~~observations~~observed variables, e.g., surface pressure (Table 1). Except for ~~no~~ its lack of the assimilation of surface pressure, ERA-20CM ~~has~~ employs the same forecast model and external forcings as ERA-20C (Table 1)~~, so~~; thus, the inclusion of ERA-20CM ~~here~~ in this study will provide ~~an~~ insight into the suitability of current atmospheric reanalyses in ~~regional warming studies~~studies of regional warming. The reanalyses adopt different sea surface temperatures (SSTs) and sea ice concentrations for different time periods, ~~maybe leading~~which may lead to temporal discontinuities in the climate signals derived from the reanalyses (Table 1). To address this issue, the boundary conditions in ~~the~~ CFSR ~~is~~

are ~~generated by~~derived from its coupled ocean-sea ice models instead of ~~the~~ observations (Table 1). ~~The~~ CFSR, NOAA 20CRv2c and NOAA 20CRv2 use ~~the~~ monthly greenhouse gases (GHGs) with annual means near ~~the~~ those used in CMIP5~~;~~. On the other hand, in ~~the~~ ERA-Interim~~ has a slower increase of~~, the GHGs increase more slowly than in ~~the~~ CMIP5 after 2000~~;~~. Finally, ~~the~~ NCEP-R1 and NCEP-R2 adopt constant global mean concentrations of the GHGs (Table 1).

The forecast model is a fundamental component of a reanalysi~~i~~s that provides the background fields to the assimilation system. ~~The~~ Different reanalyses ~~in an~~produced by a single institute generally use similar~~ but updated~~ physical parameterizations; however, updated versions of these parameterizations and higher spatial resolutions are used in the newer generations of these realizations (Table 1). The assimilation methods adopted by the current reanalyses incorporate variational methods (3D-Var and 4D-Var) and the ~~Ensemble~~ ensemble Kalman f~~F~~ilter (EnKF) approach (Table 1).

The 2-m T_a in NCEP-1, NCEP-2, MERRA, MERRA-2, ERA-20C, ERA-20CM, CERA-20C, NOAA 20CRv2c, NOAA 20CRv2 and CFSR are model-derived fields~~ as a~~ that are functions of the surface skin temperature~~ and the~~, the temperature at the lowest model level, the vertical stability and the surface roughness~~ that were~~, which ~~are primarily~~ constrained primarily by observations of upper~~-~~ air variables and the surface pressure (Kanamitsu et al., 2002~~;~~; Rienecker et al., 2011~~;~~; Reichle et al., 2017~~;~~; Poli et al., 2016~~;~~; Hersbach et al., 2015~~;~~; Laloyaux et al., 2016~~;~~; Compo et al., 2011~~;~~; Saha et al., 2010). ~~Yet,~~ However, the T_a ~~values~~ in ERA-Interim and JRA-55 ~~are~~

~~post-processing products by~~~~result from~~are post-processing ~~performed~~products by~~using~~ a relatively simple ~~analysis interpolation~~analysis scheme between the lowest model level and the surface and are~~,~~ ~~analyzed~~analysed ~~with~~ using ~~some~~ ground-based observations of T_a~~, with the help of~~ ~~combined~~ with the help of Monin-Obukhov similarity profiles consistent with the model's parameterization of the surface layer (Dee et al., 2011b~~;~~; Kobayashi et al., 2015). Additionally, radiation calculations are diagnostically determined from the prognostic cloud condensate microphysics parameterization, and the cloud macrophysics parameterization assumes a maximum-random cloud overlapping ~~scene~~ scheme (Saha et al., 2010~~;~~; Dolinar et al., 2016).

2.3 Method Used to Homogenize the Observed Time Series

~~The p~~Problems related to the observational infrastructure (e.g., instrument ~~aging~~ ageing and changes in observing practices) and station relocations can also lead to false ~~time~~ temporal heterogeneity in time series. Therefore, ~~it's~~ it is necessary to diminish the impact of data homogenization on the trends in the observed variables during the study period of 1979-2010.

We use~~d~~ the RHtestsV4 software package (Wang and Feng, 2013) to detect and homogenize the breakpoints in the monthly time series. The package ~~involves~~ includes two algorithms~~:~~. Specifically, the PMFred algorithm is based on the penalized maximal F-test (*PMF*) without a reference series (Wang, 2008), and the PMTred algorithm is based on the penalized maximal t-test (*PMT*) with a reference series (Wang et al., 2007).

In this study, we first use~~d~~ the PMFred algorithm to ~~find~~ identify potential reference series at the 95% ~~significant level~~significance level. ~~Then, we~~ We then reconstruct~~ed~~ homogenous series for each inhomogeneous series ~~by~~ using the following steps: 1) horizontal and vertical distances from the inhomogeneous station of less than 1100~~0km~~ km ~~horizontally distant from the inhomogeneous station~~ and 5000~~0m~~ m ~~vertical height difference~~, respectively, are specified~~;~~ ; 2) correlation coefficients~~ over 0.9~~ ~~of~~ between the first-order difference in the homogeneous series with that in the inhomogeneous one exceeding 0.9 are required~~;~~ ; and 3) the first ten homogeneous series ~~was~~ are ~~inverse-distance-weightedly averaged~~averaged using inverse distance weighting ~~as~~ to produce a reference series for the inhomogeneous ~~one~~station. Finally, we ~~applied~~ apply the PMTred algorithm to test ~~all the~~all of the inhomogeneous series ~~with~~ using the nearby reference series ~~nearby~~. Several intensive ~~researches~~studies ~~were~~have been conducted ~~to show a~~that indicate ~~good performance of~~ the PMTred algorithm displays good performance ~~-~~in detecting change points ~~of~~ in inhomogeneous series (Venema et al., 2012~~;~~; Wang et al., 2007).

If ~~the~~ a breakpoint is found to be statistically significant, the quantile-matching (QM) adjustment in RHtestsV4 is recommended for making adjustments to the time series (Wang et al., 2010~~;~~; Wang and Feng, 2013)~~, based on~~; in such cases, the longest available segment from 1979 to 2010 is used as the base segment. The QM adjustment aims to match the empirical distributions from all of the detrended segments with that of the specific base segment (Wang et al., 2010). In addition, we replicate~~d~~ the procedures above for the sparsely distributed ~~sparse~~ stations over western China ~~and Tibetan~~and the Tibetan Plateau.~~. Recently, t~~ The PMTred algorithm ~~with~~ and the QM adjustment ~~was~~ have recently been ~~successfully~~ used successfully to homogenize climatic time series (Aarnes et al., 2015~~;~~; Tsidu, 2012~~;~~; Dai et al., 2011~~;~~; Siswanto et al., 2015~~;~~; Wang and Wang, 2016~~;~~; Zhou et al., 2017).

As such, the significant breakpoints ~~over 1092 out of 2193 (49.8%) stations~~ ~~were~~are detected and adjusted at a confidence level of 95% at 1092 of the 2193 (49.8%) stations for the T_a time series~~,~~; 1079 ~~out of~~of the 2193 (49.2%) stations for the R_s time series~~,~~; 64 ~~out of~~of the 2193 (2.9%) stations for ~~precipitation frequency~~the ~~frequency of precipitation~~precipitation frequency time series~~,~~; 971 ~~out of~~of the 2193 (44.2%) stations for the L_d time series~~,~~; 944 ~~out of~~of the 2193 (43.0%) stations for the water vapor pressure time series~~,~~; and 956 ~~out of~~of the 2193 (43.6%) stations for the cloud fraction time series.

2.4 Trend Calculations, Partial Linear Regression, and Total Least Squares

The bias, ~~root-mean-square~~ root mean squared error (*RMSE*), standard deviation and correlation coefficient (*r*) ~~were~~are used to assess the absolute value of T_a. The trends in T_a~~Trends in T_a~~ and the relevant variables ~~were~~are calculated using the ordinary least squares method (OLS) and the two-tailed Student's *t*-test. To determine whether the reanalyses contain ~~trend bias~~biases in these trends ~~exists in reanalysis~~, the two-tailed Student's *t*-test ~~was~~is also applied to the differences ~~of~~ in the time series between the reanalys~~e~~is and the homogeneous observations.

The partial least squares approach ~~was~~is used to investigate the net relationship ~~of~~

between the detrended T_a values ~~with~~and the relevant variables (R_s, L_d and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency) after statistically excluding the confounding effects among the relevant variables (Zhou et al., 2017). To evaluate the potential ~~colinear~~collinearity of independent variables in the ~~regress model~~regression model, the variance inflation factor (*VIF*) ~~was~~is calculated. The *VIFs* for R_s, ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d ~~were~~are less than 4~~, e.g.,~~. Specifically, the *VIF*~~s of~~ for China of 2.19~~ for China,~~ is much less than the threshold of 10, above which the collinearity of ~~the regress model~~regression models is bound to adversely affect the regression results (Ryan, 2008).

The Pearson correlation ~~analysis~~ coefficient ~~was~~is used to reveal the spatial relationship ~~of~~ ~~T~~between T_a ~~with relevant variables~~and the relevant variables. To further investigate the relationship ~~of~~ between the spatial distributions of the ~~T_a trend biases~~biases in the trends in T_a ~~with~~ and the relevant parameters among the twelve reanalysis products, the weighted total least squares (WTLS) ~~metric~~ ~~was~~is adopted, in which the spatial standard deviations and correlations of ~~both~~ pairs of variables ~~at~~ on 1°×1° ~~grids~~grid cells ~~were~~ are included (Reed, 1989~~;~~; York et al., 2004~~;~~; Golub and Van Loan, 1980~~;~~; Hyk and Stojek, 2013~~;~~; Tellinghuisen, 2010):

$$\omega(x_i) = 1 \big/ \hat{\sigma}_{x_i}^2 \tag{1}$$

$$\omega(y_i) = 1 \big/ \hat{\sigma}_{y_i}^2 \tag{2}$$

$$W_i = \frac{\omega(x_i)\cdot\omega(y_i)}{\omega(x_i) + b^2\omega(y_i) - 2b\cdot r_i\sqrt{\omega(x_i)\cdot\omega(y_i)}} \tag{3}$$

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$$U_i = x_i - \sum_i^n (W_i \cdot x_i) \Big/ \sum_i^n (W_i) \tag{4}$$

$$V_i = y_i - \sum_i^n (W_i \cdot y_i) \Big/ \sum_i^n (W_i) \tag{5}$$

$$\beta_i = W_i\left[\frac{U_i}{\omega(y_i)} + \frac{b \cdot V_i}{\omega(x_i)} - (b \cdot U_i + V_i)\frac{r_i}{\sqrt{\omega(x_i) \cdot \omega(y_i)}}\right] \tag{6}$$

$$b = \frac{\sum_{i=1}^{n} W_i \cdot \beta_i \cdot V_i}{\sum_{i=1}^{n} W_i \cdot \beta_i \cdot U_i} \tag{7}$$

where x_i and y_i are the median trends in x and y ~~variable~~ (~~including~~ e.g., T_a and~~,~~ R_s ~~and so on~~) ~~at~~ for the i^{th} reanalysis product;~~,~~ $\hat{\sigma}_{x_i}$, $\hat{\sigma}_{x_i}$ and r_i are the spatial standard deviations and correlations of the trends in x and y ~~variables at~~ for the i^{th} reanalysis product;~~,~~ β_i is the least-squares-adjusted value ~~and~~; W_i is the weight of the residual error;~~,~~ and b is the slope estimated by iterative methods with a relative tolerance of 10^{-16}.

The Monte Carlo method with 10000 experiments ~~was~~is applied to estimate the 90% confidence intervals of the slope b. In the Monte Carlo method, the grid index for the 1°×1° grid cells over China ~~is generated as random number, i.e., the~~, which ranges from 1 to -691, ~~grid index for the 1°×1° grids over China~~ is generated as a random number~~, based on which we could~~ . On this basis, we can sample the spatial pattern in the ~~trends biases in~~biases in the trends in T_a, R_s, L_d and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency. ~~Then, we calculated~~We then calculate the median trends and their spatial standard deviations and correlations for each experiment~~,~~ used in the WTLS.

3. Results

3.1 Dependency of Surface Air Temperature Differences~~Biases~~ on Elevation Differences ~~Dependency of Surface Air Temperature Bias~~

Fig. 1 illustrates the differences in T_a from the NWP-like reanalyse~~i~~s and climate reanalyse~~i~~s relative to the homogenized station-based observations over China during the ~~period 19~~period of 1979-2010. ~~If directly compare~~When the T_a values measured at the stations are compared directly with those ~~at~~ in the corresponding model ~~grids~~grid cells~~ and stations~~, the results indicate that the reanalysis products ~~exhibit an underestimated~~ underestimate T_a over most of the regions ~~of~~ in China (by -0.28 ℃ to -2.56 ℃~~ in China~~)~~, especially~~. These discrepancies are especially pronounced over the Tibetan Plateau~~ (-2.75 ℃ to -7.00 ℃)~~ and Middle China, where the underestimation ranges from-2.75 ℃ to -7.00 ℃ and from ~~(~~-1.19 ℃ to -2.91 ℃, respectively~~)~~ (Fig. 1 and Table 2). A homogeneous adjustment of 0.0~~3 ℃~~3 ℃ from the raw T_a observations is insufficient to cancel the underestimation of T_a by the reanalyses (Fig. 1 and Table 2). ~~The s~~Similar ~~results of~~biases in T_a within various regions worldwide ~~bias~~ have been widely reported by previous studies~~ over regions worldwide~~ (Mao et al., 2010~~;~~; Pitman and Perkins, 2009~~;~~; Reuten et al., 2011~~;~~; Wang and Zeng, 2012~~;~~; Zhou et al., 2017~~;~~; Zhou and Wang, 2016a).

However, we found that the spatial patterns in the differences in T_a are well correlated with the elevation differences between models and stations, as reflected by ~~with~~ correlation coefficients (r) of 0.85 to 0.94 (Figs. 2 and S1)~~, which is in~~. These results are in accordance with the reports from NCEP-R1, NCEP-R2 and ERA-40 (You et al., 2010~~;~~; Ma et al., 2008~~;~~; Zhao et al., 2008). The elevation differences (ΔHeight~~, Fig~~; Figs. 2 and S1) between the stations and the model grids consists of the filtering error in the elevations used in the spectral model ~~elevations~~ (Δf) and differences in the site-to-grid elevations (Δs) due to the complexity of the orographic topography~~y~~. We further ~~quantified~~ quantify ~~their~~ the relative contributions of these factors to the T_a differences. The elevation differences can explain approximately 80% of the T_a differences~~, among which~~; approximately 74% is ~~from~~ produced by the site-to-grid elevation differences, and approximately 6% is ~~from~~ produced by the filtering error in the elevations used in the spectral model ~~elevations~~ (Fig. 2).

~~One can find that t~~The ~~regressed coefficient~~regression coefficient of the differences in T_a is approximately 6 ℃/1~~1km~~ km, ~~near~~ which is similar to the lapse rate at the surface (Fig. 2). ~~The l~~Lapse rate values ~~over~~ that exceed 6 ℃/1~~1km~~ km can be seen ~~over Tibetan~~over the Tibetan Plateau (shown as red dots in Fig. 2~~, in red dots~~). This result is very consistent with the reported lapse rates over China (Li et al., 2015~~;~~; Fang and Yoda, 1988). In addition, the ~~decreasing rate~~ rate of decrease in the model filtering error is approximately 4 ℃/1~~1km~~ km among the ~~twelve reanalysis~~twelve reanalyses (Fig. 2). These results ~~above~~ have ~~an~~ important implications for ~~a good~~the skill ~~in the simulation of~~of the simulated T_a ~~climatology~~ climatologies of ~~T_a~~ ~~in~~ the twelve reanalyses over China.

3.2 Comparison of Regional-scale Surface Air Temperature Series

Fig. 3 shows ~~the~~ Taylor diagrams of annual T_a anomalies from the observations and reanalyses over China and its seven subregions. We ~~found~~ find that the correlations ~~of annual T_a anomalies~~ between the annual T_a anomalies in the ~~twelve reanalysis~~twelve ~~product~~reanalysis products and the observations are ~~prettily~~ reasonably strong ~~with~~, as reflected by a median r of 0.95 (Fig. 3), despite ~~of~~ the relatively weak correlations ~~over Tibetan~~over the Tibetan Plateau ~~for~~ associated with NCEP-R2 (r=0.24) and CFSR (r=0.53). The simulated time series of T_a anomalies over eastern China are depicted most accurately by the reanalyses (Fig. 3c-g).

Overall, the NWP-like reanalyses (denoted by numbers 3-7) ~~have a~~display better skill than the climate reanalyse~~i~~s (denoted by numbers 8-14) ~~at this aspect~~in this regard (Fig. 3). ~~The~~ ERA-Interim and JRA-55 ~~has~~ display the best performance in the simulated time series of T_a anomalies over China (r=1.00, RMSE=0.05 ℃) and the seven regions (r=0.98, RMSE=0.1 ℃) (Fig. 3), ~~may be~~perhaps due to ~~their analysis~~the ~~incorporation~~their analysis of surface air temperature observations in ERA-Interim and JRA-55 (Table 1).

Compar~~ed with~~ing the T_a values from MERRA2 ~~to~~ and MERRA shows that~~,~~ ~~we found that the~~ MERRA2 ~~has an~~displays improved performance over n~~N~~orthern China ~~by an~~, as reflected by an ~~increasing~~ increase in the correlation coefficient of 0.1 and a reduction in the~~ed~~ RMSE of 0.1 ℃ (Fig. 3)~~, maybe~~. This result may occur because ~~the~~ MERRA2 includes~~d~~ ~~the~~ time-varying aerosol loadings (Balsamo et al., 2015~~;~~; Reichle et al., 2011). However, ~~this circumstance~~the incorporation of this information does not improve the results over Southeast China (Fig. 3~~3h~~h).

~~The~~ CERA-20C ~~has a~~ displays better performance than ERA-20C and

ERA-20CM, ~~may be~~ perhaps related to ~~an~~ the inclusion of coupled climate forecast models and data assimilation, as well as the assimilation of surface pressure ~~assimilated~~ data in CERA-20C (Fig. 3 and Table 1). ~~The~~ NOAA 20CRv2c and NOAA 20CRv2 ~~have a~~display moderate performance in this ~~aspect~~ regard (r=0.8, RMSE=0.~~3 ℃~~3 ℃) (Fig. 3), and the former reanalysis ~~has~~ displays no improvement in~~d~~ performance, despite ~~of the~~ its use of new boundary conditions (Compo et al., 2011).

3.3 Key Factors Regulating Regional Temperature Change

This section discusses key factors ~~controlling~~ that control regional temperature change from ~~a~~ the perspective of energy balance and its partitioning. The R_s heats the surface, and the portion of this radiation that becomes the sensible heat flux ~~surface~~ heats the air near the surface ~~by partitioning into sensible heat flux~~ (Zhou and Wang, 2016a~~;~~; Wang and Dickinson, 2013~~;~~; Zhou and Wang, 2016b). ~~The p~~Part of the energy absorbed by the surface is released back to s~~S~~pace as outgoing longwave radiation~~,~~ ~~some of which~~; some of this radiation is reflected by clouds and is influenced by atmospheric water ~~vapor~~vapor, further warming the near-surface air (Wang and Dickinson, 2013)~~,~~. This process is known as the greenhouse effect ~~(quantified by the L_d)~~ on T_a and is quantified by L_d. Existing studies have suggested that ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~is a better factor in quantifying~~better represents the interannual ~~variability of~~variability in soil moisture ~~over~~ in China than the precipitation amount (Wu et al., 2012~~;~~; Piao et al., 2009~~;~~; Zhou et al., 2017~~;~~; Zhou and Wang, 2017a)~~, and then~~; in turn, soil moisture ~~changes~~ affects vegetation growth and ~~surface characteristics~~ drives changes in surface characteristics (~~e.g.~~ e.g., surface albedo and roughness). These changes ~~would~~ alter the partitioning of available energy ~~for regulating~~and thus regulate ~~the~~ changes in T_a.

Figs. 4 illustrates the partial relationships between the annual anomalies in T_a and R_s ~~anomalies~~, ~~the precipitation frequencyfrequency of~~ precipitation frequency and L_d~~. Results~~$_d$. The results show that ~~the~~ T_a ~~has~~ is consistently positively ~~correlations~~ correlated with ~~the~~ R_s (except over the Tibetan Plateau) and L_d~~, but has~~; however, it is consistently negatively ~~correlations~~ correlated with ~~precipitation frequencythe frequency of precipitation~~precipitation frequency in the observations and the ~~twelve reanalysis~~twelve ~~product~~reanalysis products (Fig. 4). Based on the observations, the interannual ~~variance of~~variations in T_a ~~is~~ are jointly determined by ~~precipitation frequencythe frequency of precipitation~~precipitation frequency and L_d in Northeast China and the northern part of Northwest China (Fig. 4). All of the reanalyses roughly capture these factors over these regions, ~~even~~ although ~~having~~ they display differences in the relative magnitudes (Fig. 4). Specifically~~, i.e.,~~ ERA-20CM, NOAA 20CRv2c, NOAA 20CRv2 and CFSR exhibit ~~comparably~~ comparable relationships of T_a with ~~precipitation frequencythe frequency of precipitation~~precipitation frequency and L_d~~, but~~; however, MERRA, MERRA2, NCEP-R2, ERA-20C, and CERA-20C ~~exhibit overestimated~~overestimate the relationship~~s of~~ between T_a ~~with~~ and ~~precipitation frequencythe frequency of precipitation~~precipitation frequency, and ERA-Interim, JRA-55, and NCEP-R1 ~~present overestimated~~ overestimate the relationship~~s~~ of T_a with L_d over these regions (Fig. 4).

Over the North China Plain and Middle China, the interannual ~~variance of~~variations in T_a ~~is~~ are jointly determined by R_s, ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d (Fig. 4). The reanalyses roughly capture the effects of these three factors on T_a~~, despite of~~, although they display diverse combinations (Fig. 4). Among these combinations, ~~the~~ JRA-55, MERRA2, ERA-20CM and ERA-Interim ~~is~~ are comparable to the observations over these regions (Fig. 4). Over Southeast China, the interannual ~~variance of~~variations in T_a ~~is~~ are primarily regulated by L_d, ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and R_s (Fig. 4). The reanalyses exhibit slightly overestimated relationships of T_a with R_s and underestimated relationships with ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (Fig. 4).

~~Over Tibetan~~Over the Tibetan Plateau, the interannual ~~variance of~~variations in T_a ~~is~~ are regulated by R_s and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (Fig. 4). ~~Most reanalys~~Most of the reanalyses roughly capture the combinations of these factors~~,~~ but exhibit ~~a~~ certain differences in the relative ~~impact~~ effects of R_s and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency on T_a (Fig. 4). MERRA, MERRA2, NOAA 20CRv2c and NOAA 20CRv2 overestimate the relationships of T_a with R_s ~~over Tibetan~~over the Tibetan Plateau (Fig. 4).

Overall, the spatial patterns of the simulated partial correlation of T_a with R_s in the reanalysis products are significantly correlated with those ~~from~~ seen in the observations~~ (~~; r=0.13-0.35~~, ~~ (p<0.05) for the NWP-like reanalyse~~i~~s~~ and~~, and larger values of r=0.24-0.41~~, ~~ (p<0.05) are obtained for the climate reanalys~~is)~~es~~, and~~. Moreover, the spatial patterns in the sensitivity of T_a to R_s exhibit ~~the~~ significant correlations (r=0.12-0.17, p<0.05) for ~~most climate reanalys~~most of the climate reanalyses ~~(r=0.12-0.17, p<0.05)~~ (Table 1). ~~The frequency of precipitation~~Precipitation frequency ~~T~~ displays the largest spatial correlations (r=0.16-0.43, p<0.05) of the sensitivity of T_a ~~to~~ with these three relevant parameters in the reanalyses ~~is found to the precipitation frequency (r=0.16-0.43, p<0.05)~~ (Table 3). ~~The s~~Significant spatial correlations ~~of~~ reflecting the relationship~~s~~ (including the partial correlation and sensitivity) of T_a with L_d ~~were~~are also found (Table 1).

3.4 Regional Warming Trend Biases and Their Causes

From 1979 to 2010 over China, ~~The~~ T_a exhibits strong warming trends of 0.3~~7 ℃~~7 ℃/decade (p<0.05) in~~from~~ the observations and 0.22-0.4~~8 ℃~~8 ℃/decade (p<0.05) ~~among~~ in the twelve reanalyses ~~from 1979 to 2010 over China~~ (Figs. 5 and S2-S3, Table 2). ~~The~~ ERA-Interim and JRA-55 ~~have~~ display spatial correlations with the observations (r=0.47 and 0.54, p<0.05) that are due at least partly ~~due~~ to the inclusion of some T_a observations, whereas NCEP-R2 and ERA-20C ~~perform~~ display the worst performance (Figs. S3, Tables 1 and 3). Furthermore, approximately 87% of the observed trends in T_a ~~trend~~ over China can be explained by the greenhouse effect (i.e., 65% can be explained by the trend in L_d~~, 65%~~), ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (29%) and R_s (-7%, due to the trend in radiative forcing of -1.1 W·m^{-2}/decade) (Figs. S3-4). The influence of the greenhouse effect on~~f~~ the observed trends in T_a ~~trend mainly~~ consists mainly of the trends in the atmospheric water vapor (42%) and the cloud fraction (3%) (Fig. S5). Among the reanalyses, over 90% of the ~~T_a trends~~trend in T_a can be explained ~~by greenhouse~~by the greenhouse effect, ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and R_s (Figs. S4-6). Specifically, ERA-Interim, JRA-55, MERRA and MERRA2 ~~present~~ display the best ability ~~of capturing~~to capture the~~se~~ contributions of the greenhouse effect (48% to 76%), ~~the frequency of precipitation~~precipitation frequency (22% to 34%) and R_s (-4% to 13%) to the ~~T_a trend~~trend in T_a over China~~, from greenhouse effect (48% to 76%), the precipitation frequency (22% to 34%) and R_s (-4% to 13%)~~ (Figs. S4 and S6). The remaining NWP-like reanalyses (i.e., NCEP-R1 and NCEP-R2) ~~largely~~ substantially overestimate the~~d~~ contribution –of ~~the~~ R_s to the ~~T_a trend~~trend in T_a, whereas the climate reanalyses overestimate the contribution~~d that~~ from ~~the~~ L_d (Figs. S4 and S6).

However, ~~the~~ averaged trends ~~across a large territory~~over large areas may mask ~~regionally different~~regional differences~~ values, reflecting~~ that reflect diverse regional warming biases and their causes (Figs. 5-7).~~ Evidently,~~ The mean-adjusted spatial patterns of the ~~trend biases in~~biases in the trends in T_a ~~show consistency~~appear to be consistent among the twelve reanalyses (Fig. S7) and mimic the spatial patterns in the overestimated R_s trends over the North China Plain, South China and Northeast China (Fig. S8), ~~with~~ given the~~ir~~ spatial correlations between these variables in ~~most reanalys~~most of the reanalyses (r=0.11-0.42, p<0.05) (Figs. 6 and S7-8, Table 3). ~~Howbeit~~However, the reanalyses still underestimate the ~~T_a trend~~trends in T_a over most of the regions~~, one of important reasons for which~~. The key reason for this underestimation ~~is~~ is the increase in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency over Northwest China, the Loess Plateau, and Middle China ~~for~~ seen in the NWP-like reanalyses and that seen over ~~boarder~~ broader regions ~~for~~ in the climate reanalyses (Figs. 5-6 and S9). This relationship is reflected by their negative spatial correlation~~, with~~ which has a maximum value of -0.62 (p<0.05)~~,~~ for MERRA~~)~~ (Table 3). Moreover, the decrease in L_d, which occurs due to the decreases in the atmospheric water vapor and cloud fraction that occur in the NWP-like reanalyses (Figs. S10-12), substantially cancels the warming effect of the ~~overestimated~~ overestimation of R_s on T_a over eastern China (Figs. 5 and S7). The opposite changes occur over Southeastern China in the climate reanalyses (Figs. 5 and S10). ~~This~~ The effect of the changes in L_d is reflected by ~~their~~ its spatial correlations of up to 0.50 (p<0.05) (Table 3).

Here, we further ~~quantified~~ quantify the contributions ~~of~~ to the ~~trend biases in~~biases in the trend in T_a made by those in R_s, L_d and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency among the twelve reanalyses over China and its seven subregions (Figs. 6-7). Over China, the overestimated R_s trends (by 0.00-3.93 W·m^{-2}/decade~~, Fig~~; Figs. S8 and S13) ~~can~~ increase the ~~T_a trends~~trends in T_a (by 0.02-0.16 ℃/decade~~, Fig~~; Fig. 7) ~~in twelve~~in the twelve reanalyses; the~~,~~ underestimated L_d trends (by -0.25 to -1.61 W·m^{-2}/decade for the NWP-like reanalyses~~, Fig~~; Figs. S10 and S15) ~~can~~ decrease the ~~T_a trends~~trends in T_a (by -0.05 to -0.25 ℃/decade for the NWP-like reanalyses~~, Fig~~; Fig. 7); and the biases in

~~precipitation frequency~~the trends in ~~the frequency of precipitation~~precipitation frequency~~ trends biases~~ (by approximately -1.5 days/decade for the NWP-like reanalyses and approximately 2.6 days/decade for the climate reanalyses~~, Fig~~; Figs. S9 and S14) ~~can~~ decrease the ~~T_a trends~~trends in T_a (by 0.01 to 0.05 ℃/decade for the NWP-like reanalyses and -0.01 to -0.06 ℃/decade for the climate reanalyses~~, Fig~~; Fig. 7)~~, which jointly~~. Together, these effects produce an underestimate in the~~ make the T_a trends~~trends in T_a ~~underestimated by~~on the order of 0.10 ℃/decade ~~in reanalys~~in the reanalyses (Fig. 7 and Table 2).

Over northern China, ~~trend biases in~~biases in the trend in T_a ~~primarily~~ result primarily from those in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d (Figs. 6-7). Over Northeast China~~, observations~~, the observations exhibit an amplified warming of 0.4~~1 ℃~~1 ℃/decade (p<0.05~~, Fig~~; Fig. 4 and Table 2)~~, which~~. This warming is significantly underestimated by NCEP-R1, JRA-55, NOAA 20CRv2 and NOAA 20CRv2c (by on the order of -0.15 ℃/decade) and is overestimated by MERRA and CFSR (by on the order of 0.2 ℃/decade) (Figs. 6-7). These ~~T_a trend biases~~biases in the trends in T_a ~~in reanalys~~in the reanalysis are jointly explained ~~with~~ by the warming (0.04-0.48 ℃/decade) induced by the underestimated trends in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and the cooling (-0.04 to -0.42 ℃/decade) induced by the underestimated trends in L_d (Fig. 7).

Over Northwest China, the ~~trend biases in~~biases in the trend in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d are mainly

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explained by the overestimated warming in NCEP-R2 (by 0.22 ℃/decade) (Fig. 7). ~~Largely~~The substantially underestimated trend in L_d induced by the decrease in the atmospheric water vapor and cloud fraction (Figs. S9-S12 and S16-17)~~,~~ lead~~s~~ to an ~~underestimated~~ underestimate of the warming in MERRA (by -0.22 ℃/decade) (Fig. 7).

~~Most reanalys~~Most of the reanalyses ~~present a~~display ~~weakening~~ weakened warming ~~over Tibetan~~over the Tibetan Plateau and the Loess Plateau (Fig. 5 and S3, Table 2). ~~More evidently~~In particular, NCEP-R1 and NCEP-R2 fail to reproduce the warming ~~over Tibetan~~over the Tibetan Plateau, and MERRA fails to reproduce the warming over the Loess Plateau (Fig. 5 and S3, Table 2). The significant cooling ~~trend biases in~~biases in the trends in T_a (by -0.02 to -0.31 ℃/decade) over the Tibetan Plateau ~~and Loess Plateau~~and the Loess Plateau result from the underestimated trends in L_d and the overestimated trends in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency seen in ~~most reanalys~~most of the reanalyses (Figs. 5-7 and S9-12). ~~This~~ These cooling biases are further induced by the underestimated trends in R_s (Figs. 5-7 and S8).

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Over southern China, the ~~trend biases in~~biases in the trend in T_a are regulated by the ~~trend biases~~biases in the trends ~~those~~ in R_s, L_d and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (Figs. 6-7). Over Southeast China, the significantly overestimated ~~significant overestimated~~ trends in T_a~~trends in T_a~~ (by 0.04, 0.02 and 0.17 ℃/decade, respectively) are induced by the ~~by~~ overestimated trends in R_s (by 4.25, 3.34 and 6.27 W·m^{-2}/decade, respectively) seen in ERA-Interim, JRA-55 and CFSR (Figs. 6-7 and S8). The underestimated trends in T_a~~trends in T_a~~ are induced by the overestimated trends in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d in NCEP-R1, MERRA, ERA-20CM, CERA-20C, NOAA 20CRv2 and NOAA 20CRv2c (Figs. 6-7 and S9).

Over Middle China, the ~~significant over~~significantly overestimated trends in T_a~~trends in T_a~~ (by 0.04, 0.06, 0.11, 0.03, 0.11 and 0.14 ℃/decade, respectively) are induced by the overestimated trends in R_s (by 2.09, 1.50, 2.59, 1.20 and 4.81 W·m^{-2}/decade, respectively) seen in ERA-Interim, JRA-55, ERA-20C, ERA-20CM, CERA-20C and CFSR (Figs. 6-7 and S8). The overestimated trends in ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~could~~ may lead to cooling in the trends in T_a~~trends in T_a~~ ~~in reanalys~~in the reanalyses, especially for MERRA (which reflects an induced bias in the trend of -0.1~~5 ℃~~5 ℃/decade~~ of the induced trend bias~~) over Middle China (Figs. 6-7 and S9).

Due to the underestimated trends in the atmospheric water vapor and the cloud fraction (Figs. S11-12), the underestimation of ~~the~~ L_d ~~is underestimated to have~~produces a cooling effect on the ~~T_a trend~~trend in T_a (by -0.05 to -0.32 ℃/decade) ~~in reanalys~~in the reanalyses over the North China Plain (Figs. 6-7 and S10). However, due to the lack of inclusion of ~~the~~ plausible trends in aerosol loading, the substantial increases in R_s ~~over North~~over the North China Plain (Fig. S8) have ~~a~~ strong warming effects on the ~~T_a trend~~trends in T_a (by 0.01 to 0.21 ℃/decade) ~~in reanalys~~in the reanalyses (Figs. 6-7 and S8). The ~~trend biases in~~biases in the trends in ~~precipitation~~

~~frequency~~~~the frequency of precipitation~~precipitation frequency (~~by~~ of approximately -2.5 days/decade for the NWP-like reanalyses and approximately 1.5 days/decade for some of the climate reanalyses) contribute some part of the ~~trend biases in~~biases in the trends in T_a (~~by~~ approximately 0.05 ℃/decade for the NWP-like reanalyses and -0.03 ℃/decade for the climate reanalyses).~~ ~~

Overall, the ~~trend biases in~~biases in the trends in T_a ~~in reanalys~~in the reanalyses can be substantially explained by those in L_d, ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and R_s, but~~ it varies~~ this effect varies~~ by~~ regionally~~s~~ (Figs. 6-7). Over northern China, the ~~trend biases in~~biases in the trend in T_a ~~(by order of~~(which are on the order of -0.12 ℃/decade)~~ primarily~~ result primarily from a combination of those in L_d ~~(by order of~~(which are on the order of -0.10 ℃/decade) and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~(by order of~~(which are on the order of 0.05 ℃/decade), with relatively small contributions from R_s ~~(by order of~~(which are on the order of -0.03 ℃/decade). Over southern China, the ~~trend biases in~~biases in the trend in T_a ~~(by order of~~(which are on the order of -0.07 ℃/decade) are caused by those in R_s ~~(by order of~~(which are on the order of 0.10 ℃/decade), L_d ~~(by order of~~(which are on the order of -0.08 ℃/decade) and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~(by order of~~(which are on the order of -0.06 ℃/decade) (Fig. S18). Note also that the ~~analyses~~ incorporation of the ~~observation~~ observed changes ~~of~~ in surface air temperatures in ERA-Interim and

JRA-55 may ~~bring~~ introduce ~~trend biases in~~biases into the trends in the output~~ of~~ T_a values~~, but~~; however, the use of partial correlation and regression analysis would lead to ~~their~~ smaller impacts of the biases in these physical variables in quantifying their contributions~~ of the T_a trend biases~~ to the trends in T_a~~ by the physical variables above~~.

3.5 Spatial Linkages of ~~Warming Trend Biases~~Biases in the Warming Trends ~~among~~ in the Twelve Reanalyses

~~By i~~We next integrate~~ntegrating~~ the relationships of the spatial patterns in the ~~T_a trend biases~~biases in the trends in T_a with those in R_s, L_d and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency over China ~~among~~ in the twelve reanalyses (Fig. 8)~~, it was found~~. The results show that the ~~trend biases in~~biases in the trends in T_a show significant correlations with R_s (r=0.80, slope=0.06, p=0.09) and~~,~~ ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (r=-0.83, slope=-0.04, p=0.02) and L_d (r=0.77, slope=0.10, p=0.10) ~~among~~ in the twelve reanalyses~~,~~ if~~ include the~~ information on~~f~~ these patterns is included. ~~Without considering~~When the spatial patterns of the ~~trend biases in~~biases in the trends in these variables are not considered, the ~~T_a trend biases~~biases in the trends in T_a show relatively small~~ler~~ correlations with R_s (r=0.32, slope=0.02, p>0.1), ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (r=-0.51, slope=-0.02, p=0.09) and L_d (r=0.14, slope=0.02, p>0.1) ~~among~~ in the reanalyses (Fig. 8). ~~The same~~Similar ~~circumstances occur~~results are obtained for the atmospheric water vapor (r=0.71, p=0.1) and the cloud fraction (r=-0.74, p=0.09) if ~~consider~~ their spatial patterns are considered (Figs. S19), and this relationship ~~from~~ involving the cloud fraction is very similar to that ~~from the~~associated with R_s (Figs. 8 and S19). ~~Over~~ Within the ~~China's subregions~~subregions of China, the ~~trend biases in~~biases in the trends in T_a show significant correlations with R_s (r=068 to 0.90, p<0.1), ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (r=-0.55 to -0.94, p<0.1) and L_d (r=0.53 to 0.93, p<0.1) ~~with~~ when the ~~inclusion f~~ spatial patterns ~~among~~ in the reanalyses are included (Fig. S20). These results provide a novel ~~view to~~perspective that can be used to investigate the spatial relationships between ~~trend biases in~~biases in the trends in T_a and ~~the~~ relevant quantities ~~among~~ in ~~the~~ reanalyses.

4. Discussion

In this section, we first examine~~d~~ the possible impacts of data homogenization on the ~~T_a trend~~trends in T_a. The ~~T_a trends~~trends in T_a derived from the original dataset are almost ~~higher~~ as high as~~than~~ those from the ~~homogenous data~~homogenized dataset, especially over the North China Plain and Northwest China (Fig. 5 and Table 2). ~~This h~~Homogenization primarily adjusts ~~the~~ breakpoints in ~~the~~ time series (Wang, 2008), which occur mainly due ~~mainly due~~ to station relocation and changes in instruments (Cao et al., 2016~~;~~; Li et al., 2017~~;~~; Wang, 2014), and it~~,~~ helps to objectively depict ~~the T_a trend~~trends in T_a ~~for~~, thus permitting the assessment of the modelled ~~T_a trend~~trends in T_a and its spatial patterns that are present in the reanalyses.

We found that the elevation differences between the models and the stations ~~actually~~ influence the biases in the ~~T_a trend~~trends in T_a ~~bias, but can~~ but cannot explain the spatial patterns in ~~the T_a trend~~the biases in the trends in T_a ~~bias~~ (average~~d~~

r=0.11) (Fig. S21). ~~Compared the same-grid models~~Comparison of the models that use the same grid (NOAA 20CRv2c vs. NOAA 20CRv2, MERRA vs. MERRA2, NCEP-R1 vs. NCEP-R2 and ERA-20C vs. ERA-20CM)~~, we found the~~ shows that the one is ~~statistically~~ correlated~~s~~ with elevation differences, but the other ~~does~~ is not, which implies that this statistical correlation ~~should not be physical significance~~does not have physical significance. ~~Besides,~~ In addition, elevation differences do~~es~~ not change with time. Nevertheless, the spatial patterns in the normalized trends in T_a~~trends in T_a~~ (excluding the impacts of the absolute value of temperature on the trends) are very near to those of the trends (Fig. S22), implying ~~the impact of~~that the differences in the absolute value of temperature have an important effect ~~due to~~, given that the site-to-grid inconsistency can be neglected.

~~In reanalys~~In the reanalyses, vegetation is only included as ~~a~~ climatological information~~y~~, but the vegetation ~~has~~ displays a growth trend ~~in nature~~ during the study ~~period 19~~period of 1979-2010 ~~over~~ within China (Fig. S23)~~, which~~. This discrepancy ~~will~~ positively enlarges the ~~T_a trend biases~~biases in the trends in T_a due to the vegetation cooling effect (Zeng et al., 2017~~;~~; Trigo et al., 2015). This effect is reflected by the negative spatial correlation (r=-0.26, p=0.00) between the inverted trend in the NDVI and the ~~trend biases in~~biases in the trend in T_a (Fig. S23). The ~~vegetation growth would~~growth of vegetation ~~cool the~~reduces T_a~~near-surface air temperatures~~ by regulating surface roughness, surface conductivity, soil moisture and albedo to partition ~~more~~ greater amounts of available energy into latent heat fluxes ~~and then~~, which leads to the formation of more precipitation (Shen et al., 2015~~;~~;

Spracklen et al., 2013)~~, thereby~~. Thus, the inclusion of vegetation growth will ~~have improved effect on the~~improve the simulation of trend~~ simulations~~ ~~(~~and especially~~ for~~ the spatial pattern~~)~~ of T_a ~~in reanalysis~~in the reanalyses through~~ a~~ the incorporation of more complete physical parameterizations~~ above in reanalysis~~ (Li et al., 2005~~;~~; Dee and Todling, 2000~~;~~; Trigo et al., 2015).

Due to their inclusion of surface air temperature observations, ~~the~~ ERA-Interim and JRA-55 ~~exhibit a relatively skillful pattern~~display high skill in reproducing the observed patterns~~ with~~; they have near-zero means (0.01 and 0.01 ℃/decade) and the smallest standard deviations (0.16 and 0.15 ℃/decade) of the trend biases among the ~~twelve reanalysis~~twelve ~~product~~reanalysis products~~, albeit being still evident~~. However, pattern differences of 37.8% (standard deviation of trend bias/China-averaged t~~T~~rend) are still evident (Figs. 5 and 8). ~~Despite of no inclusion of~~Although it does not incorporate surface air temperature observations, ERA-20CM presents a pattern (with a mean of -0.04 ℃/decade and a standard deviation of 0.15 ℃/decade~~, Fig~~; Figs. 5 and 8) that is comparable to those of ERA-Interim and JRA-55~~,~~ and better than that of ERA-20C (mean of -0.08 ℃/decade and standard deviation of 0.20 ℃/decade~~, Fig~~; Figs. 5 and 8)~~ with~~, which uses the same forecast model as ERA-20CM~~, which implies~~. These results imply that~~ a potential approach of~~ ensemble forecasting could be used to meet~~ to this end~~ important goals. ~~This advantage of~~The ensemble forecasting technique used in ERA-20CM also displays advantages in that it ~~perform better in the~~yields an improved simulated pattern of ~~trend biases in R_s~~biases in the trends in R_s (SD=1.84 W m^{-2}/decade, 171%),

~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (SD=2.78days/decade, 122%) and L_d (SD=1.25 W m^{-2}/decade, 82%) (Fig. 8).

We consider~~ed to which extent~~ the degree to which the ensemble assimilation technique can improve the spatial patterns of the biases in the ~~T_a trend~~trends in T_a ~~bias in reanalys~~in the reanalyses. We ~~found~~ find that this technique can detect the ~~T_a trend biases~~biases in the trends in T_a over more another ~~more another~~ approximately 12% (8%) of the ~~grids~~grid cells ~~for~~ in CERA-20C~~ with~~, which incorporates 10 ensemble members~~s~~ (NOAA 20CR2vc and NOAA 20CR2v ~~with~~ employ 56 ensemble members~~s~~) (Figs. 5~~5l~~ l-n). However, the ~~T_a trend biases~~biases in the trends in T_a over these ~~grids~~grid cells ~~were~~are ~~detected to be~~ not ~~n-~~significant at ~~the~~ a significance level of 0.05, according to ~~for~~ Student's t-test, implying that the ensemble assimilation technique can~~-~~not explain the spatial pattern of the ~~T_a trend biases~~biases in the trends in T_a identified~~displayed~~ in this study (in Figs. 5~~5l~~ l-n).

~~To preliminarily~~To provide a preliminary discussion of the improvements ~~of~~ in climate forecast models in reflecting patterns in climate trends, we compare the~~d~~ spatial patterns of the ~~trend biases in R_s~~biases in the trends in R_s, ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d ~~without direct observations analyzed in the reanalyses~~in the reanalyses that do not incorporate observations. We ~~can~~ find that the climate forecast models, i.e., ERA-20C, ERA-20CM, CERA-20C, NOAA 20CRv2c and NOAA 20CRv2, ~~perform better~~display better performance in reproducing the pattern of ~~trend biases in R_s~~biases in the trends in R_s (mean of 1.36 vs. 2.18 W m^{-2}/decade;~~,~~ SD of 2.04 vs. 2.71

W m^{-2}/decade), ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (mean of 1.32 vs. -1.4~~4 %~~4%/decade;~~,~~ SD of 3.57 vs. 6.1~~4 %~~4%/decade) and L_d (mean of 0.12 vs. -0.85 W m^{-2}/decade;~~,~~ SD of 1.33 vs. 1.50 W m^{-2}/decade) than the NWP-like models, i.e., ERA-Interim, NCEP-R1, MERRA, JRA-55, NCEP-R2 and MERRA2 (Fig. 8). ~~Besides,~~ In addition, because the SST boundary condition~~ freely~~ evolves~~d~~ freely in CFSR, the patterns of ~~trend biases in R_s~~biases in the trends in R_s, ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and L_d in CFSR~~ substantially~~ differ substantially from those in the other reanalyses.

We also ~~considered~~ consider whether the spatial pattern of ~~trend biases in~~biases in the trend in T_a is altered by the atmospheric ~~circulations~~circulation patterns simulated by the ERA-20CM ensemble~~s~~. In ERA-20CM, the atmospheric ~~circulations~~circulation patterns are influenced ~~from~~ by SSTs and sea ice and then partly mediate the influence~~s~~ of global forcings on the ~~T_a trend~~trends in T_a. In ERA-20CM, the probability distribution function of the ~~T_a trend biases~~biases in the trends in T_a from outside the ensemble ranges incorporates that from Student's *t*-test at a significance level of 0.05 (Fig. 5k). This result has important implications in that 1) the climate variability in the~~model~~ ensembles under the different model realizations of SSTs and sea ice cover does not change the pattern of the ~~T_a trend biases~~biases in the trends in T_a (Fig. 5k)~~;~~; moreover, 2) ~~A~~ Student's *t*-test exhibits a suitable ability to detect the significance of the ~~T_a trend biases~~biases in the trends in T_a (Fig. 5k) ~~for~~ when considering the effects of interannual variability on the trend.

Overall, producing global or regional reanalyses that adequately reflect regional climate is challenging using the current strategy, and further improvements are required. The results and discussion above indicate some potential but challenging approaches that can be used to maximize the signal component corresponding to the regional climate in final reanalyses and robustly narrow the uncertainties in trends.

1) MERRA2 incorporates time-varying aerosol loadings in a pioneering attempt to improve regional warming over the North China Plain to some extent. Thus, we encourage research groups to include accurate aerosol information and improve the skill of simulation of the energy budget and partitioning, especially of regional surface incident solar radiation, in other reanalyses.

2) To improve regional climate modelling, forecast output should be produced using a physical ensemble like that employed in ERA-20CM to quantify the uncertainties associated with the relevant parameterizations in the reanalyses, due to the impossibility of optimizing all of the biases. Meanwhile, careful ensemble design would likely yield useful information for use in improving models, assimilation methods and the bias correction of observations by exploring the interdependency among sources of errors. Such designs would undoubtedly have additional benefits for further development, leading to the next generation of reanalyses.

3) To improve coupled land-atmospheric interactions, the true dynamics of land cover and use should be incorporated. Moreover, the physical parameterizations should be improved, including the responses of surface roughness, surface conductivity and albedo to regional climate. These changes would represent an

improvement over the use of constant types and fractions of vegetation, as is done in ERA-Interim (Zhou and Wang, 2016a).

4) Given the implications of the spurious performance of the freely evolving boundary conditions in CFSR, homogeneous and accurate records of SST and sea ice should be produced.

Next-generation reanalyses, including both global and regional reanalyses, will assimilate and analyse *in situ* observations, satellite radiance, and other remote observations. In addition to short-term accuracy and long-term trends, they will also focus on spatial patterns by incorporating or improving accurate representations of land surface conditions and processes within the coupled weather and climate Earth systems. Thus, these reanalyses will advance the simulation of land-atmosphere interactions to yield high skill in studies of regional warming and the detection and attribution of regional climate change using various datasets, which frequently include global and regional reanalyses (Zhou et al., 2018; Zhou and Wang, 2016c; Herring et al., 2018; Trenberth et al., 2015; Stott, 2016; Dai et al., 2017; Zhou and Wang, 2017b). Additionally, the uncertainties associated with regional warming could be ascertained using physics ensembles with various equiprobable realizations of boundary conditions.

~~4~~5. Conclusions ~~and Perspectives~~

~~Reanalyses~~ The reanalyses ~~have~~ display differences in T_a ~~referenced~~ when compared to the observations with a range of -10~10 ℃ over China~~, a~~. Approximately

74% and 6% of ~~which~~ these differences can be explained by ~~the~~ site-to-grid elevation difference~~s~~s and the filtering error in the elevations used in the spectral models ~~elevation~~. ~~This~~ These results ~~implies~~ implya fairly good skill in the simulation of the climatology of T_a in the twelve reanalyses over China. Moreover, the twelve reanalyses roughly capture the interannual ~~variability of~~variability in T_a ~~among the twelve reanalysis~~ (median r=0.95). ~~Reanalyses~~ In the reanalyses,~~exhibit that~~ T_a ~~has~~ displays a consistently positive correlation~~s~~ with ~~the~~ R_s and L_d~~,~~ and ~~has~~ is negatively ~~correlations~~ correlated with ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency, as ~~those~~ seen in observations, despite ~~of having~~the evident spatial patterns in their magnitudes over China.

~~The~~ T_a exhibits a strong warming trend of 0.3~~7 ℃~~7 ℃/decade (p<0.05) ~~from~~ in the observations and 0.22-0.4~~8 ℃~~8 ℃/decade (p<0.05) ~~among~~ in the twelve reanalyses over China. In the observations, approximately 87% of the observed trend in T_a over China can be explained by the greenhouse effect (i.e., 65% can be explained by the trend in L_d), ~~the frequency of precipitation~~precipitation frequency (29%) and R_s (-7%, due to the trend in radiative forcing of -1.1 W·m^{-2}/decade)~~approximately 87% of the observed T_a trend can be explained by greenhouse effect (i.e., trend in L_d, 65%), the precipitation frequency (29%) and R_s (-7%, due to the trend of -1.1 W·m^{-2}/decade) over China~~.

However, the ~~trends biases in~~biases in the trends in T_a ~~from~~ seen in the reanalyses relative to the observations display an evident spatial pattern (mean=-0.16~0.11 ℃/decade, SD=0.15-0.30 ℃/decade). The spatial patterns of the

~~trends biases in~~biases in the trends in the values of~~ reanalyzed~~ T_a in the reanalyses ~~have significant correlations~~are significantly correlated with those in R_s (maximum r ~~=~~=0.42, p<0.05), ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (maximum r~~ =~~=-0.62, p<0.05) and L_d (maximum r~~ =~~=0.50, p<0.05). Over northern China, the ~~trend biases in~~biases in the trends in T_a ~~(by order of~~(which are on the order of -0.12 ℃/decade)~~ primarily~~ result primarily from a combination of those in L_d ~~(by order of~~(which are on the order of -0.10 ℃/decade) and ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~(by order of~~(which are on the order of 0.05 ℃/decade), with relatively small contributions from R_s ~~(by order of~~(which are on the order of -0.03 ℃/decade). Over southern China, the ~~trend biases in~~biases in the trends in T_a ~~(by order of~~(which are on the order of -0.07 ℃/decade) are regulated by the~~ trend~~ biases ~~those~~in the trends in R_s ~~(by order of~~(which are on the order of 0.10 ℃/decade), L_d ~~(by order of~~(which are on the order of -0.08 ℃/decade) and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency ~~(by order of~~(which are on the order of -0.06 ℃/decade).

If~~ include~~ information on~~f~~ spatial patterns is included, the simulated~~ trend biases of~~ biases in the trends in T_a correlate well with those of ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency, R_s and L_d ~~among~~ in the reanalyses (r=-0.83, 0.80 and 0.77, p<0.1)~~, so they are~~; similar results are obtained for the atmospheric water vapor and the cloud fraction (r=0.71 and -0.74, p<0.1). These results provide a novel ~~view to~~perspective that can be used to investigate the spatial relationships between the ~~trend biases in~~biases in the trends in T_a and the relevant parameters among the twelve reanalyses.

~~From the observation, model and assimilation method, we comprehensively discussed their possible impact on the simulated biases in spatial pattern of the T_a trends. Overall, it's a challenge to produce a global or regional reanalysis suitable for region climate under the current strategy and to-do improvement. Based on the results above, some potential but challenging approaches arise to maximize regional climate signal component in the final reanalysis and robustly narrow the trend uncertainties:~~

~~1) As a pioneer, MERRA2 tried to incorporate time-varying aerosol loadings to improve regional warming over the North China Plain to some extent, so encourage to assimilate the accurate aerosol information and improve simulated skill of energy budget and partitioning, especially for regional surface incident solar radiation in the other reanalyses.~~

~~2) Make use of precipitation datasets with high temporal resolution from *in-situ* and satellite-based observations (Zhou and Wang, 2017a;Trenberth and Zhang, 2017;Dai et al., 2017) or the GPS water vapor (Bengtsson et al., 2003;Voosen, 2017;Poli et al., 2010) to dynamically constrain precipitation occurrence including precipitation intensity and frequency (Qian et al., 2006;Trenberth et al., 2011;Bengtsson et al., 2007;Trenberth, 2004). This, in turn, will have more accurate representations of clouds and precipitation, especially their responses to climate change (Dai et al., 2017;Zhou and Wang, 2017b).~~

~~3) Produce forecast output using a perturbed physical ensemble like ERA-20CM to quantify the uncertainty associated with relevant parameterizations in reanalyses,~~

~~due to impossibility to optimize all the biases to improve regional climate modeling. Meanwhile, careful ensemble design would probably yield useful information to improve model/assimilation and bias correction of observation by exploring interdependency among sources of errors. They would undoubtedly have additional benefit for further development pathways to the next generation of reanalyses.~~

~~4) Incorporate the true dynamics of land cover and use and improve the physical parameterizations such as the response of surface roughness, surface conductivity and albedo to regional climates, rather than constant type and fraction of vegetation as ERA-Interim (Zhou and Wang, 2016a), to improve the coupling of land-atmospheric interaction.~~

~~5) Implication from the spurious performance of freely evolved boundary conditions in CFSR, the homogeneous SST/sea ice should be reconstructed by bringing together many previous versions and new ARGO ocean observing network.~~

~~A next-generation reanalysis including global and regional reanalyses will have focus not only on short-term accuracy and long-term trends by assimilating *in-situ* observations, satellite radiances, and other remote observations, but also on their spatial patterns by incorporating or improving accurate representations of land surface conditions and processes within unified weather-climate coupled Earth systems, to advance the simulation of the land-atmosphere interactions for good skill in regional warming studies, so as for the detection and attribution of regional climate changes using various datasets and global/regional reanalyses widely included (Zhou et al., 2018;Zhou and Wang, 2016c;Herring et al., 2018;Trenberth et al., 2015;Stott,~~

~~2016;Dai et al., 2017;Zhou and Wang, 2017b). Additionally, the uncertainties of regional warming could be ascertained by perturbed model physics ensembles with various equiprobable realizations of boundary conditions.~~

Therefore, improving simulations of ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency and R_s helps to maximize the ~~regional climate signal component~~signal component corresponding to the regional climate. ~~Besides,~~ In addition, incorporating vegetation dynamics ~~in reanalys~~in reanalyses and the use of accurate aerosol information, as in MERRA-2 ~~(Modern-Era Retrospective Analysis for Research and Applications, version 2)~~, would advance the ~~regional warming modeling~~modelling of regional warming. ~~Ensemble~~ The ensemble technique ~~(~~adopted in ERA-20CM, a ~~twentieth century~~twentieth-century atmospheric model ensemble ~~without assimilating observations)~~that does not assimilate observations, significantly narrows the ~~regional warming uncertainties~~uncertainties of regional warming ~~in reanalys~~in the reanalyse~~i~~s (standard deviation=0.15 ℃/decade).

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the Global ~~Modeling~~Modelling and Assimilation Office (GMAO) at the NASA Goddard Space Flight Center for providing the MERRA and MERRA2 data (http://gmao.gsfc.nasa.gov/)~~;~~; the NOAA Earth System Research Laboratory (ESRL) for providing the NCEP-R1, NCEP-R2, CFSR, NOAA 20CRv2 and NOAA 20CRv2c data (http://www.esrl.noaa.gov/)~~;~~; and the Climate Prediction Division of the Global Environment and Marine Department at the Japan Meteorological Agency for providing the JRA-55 data (http://jra.kishou.go.jp/). We thank the Expert Team on Climate Change Detection and Indices (ETCCDI) for providing the RHtestV4 package (http://etccdi.pacificclimate.org/software.shtml), the United States Geological Survey Earth Resources Observation and Science Data Center for providing the GTOPO30 data (http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html) and the working team ~~for~~ of the Global Inventory Monitoring and ~~Modeling~~Modelling System (GIMMS) project (https://ecocast.arc.nasa.gov/data/pub/gimms/). We thank Kevin E. Trenberth for his insightful suggestions.

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Table 1. ~~Summarized~~ Summary information on the ~~twelve reanalysis~~twelve ~~product~~reanalysis products, including institution, model resolution, assimilation system, ~~included~~ surface observations included associated with surface air temperatures, sea ice and sea surface temperatures ~~/SST~~ (SSTs~~sea surface temperature~~) and ~~GHGs~~ greenhouse gas (GHG) boundary conditions. The number in the parentheses ~~of Column~~in the M~~M~~odel N~~N~~ame column is the year ~~for~~ of the version of the forecast model used. More details ~~for~~ on each product can be found in the associated reference.

Reanalysis	Institution	Model N~~N~~ame	Model R~~R~~esolution	Period	Assimilation S~~S~~ystem
ERA-Interim	ECMWF	IFS version Cy31r2 (2007)	T255 ~80 km, 60 levels	1979 onwards	4D-VAR
JRA-55	JMA	JMA operational numerical weather ~~precidition~~prediction system (2009)	T319 ~55 km, 60 levels	1958-2013	4D-VAR
NCEP-R1	NCEP/NCAR	NCEP operational numerical weather ~~precidition~~prediction system (1995)	T62 ~210 km, 28 levels	1948 onwards	3D-VAR
NCEP-R2	NCEP/DOE	Modified NCEP-R1 model (1998)	T62 ~210 km, 28 levels	1979 onwards	3D-VAR
MERRA	NASA/GMAO	~~An~~ GEOS-5.0.2 atmospheric general circulation model (2008)	0.5 °× 0.667 ° ~55 km, 72 levels	1979 onwards	3D-VAR with incremental updating~~e~~ (GEOS IAU)
MERRA-2	NASA/GMAO	~~The u~~Updated version ~~model~~ of GEOS-5.12.4 ~~as~~ used in MERRA~~; and~~ its land ~~version~~ model is similar to that of MERRA ~~land~~ (2015)	0.5 °× 0.625 ° ~55 km, 72 levels	1980 onwards	3D-VAR with incremental updating~~e~~ (GEOS IAU)
ERA-20C	ECMWF	IFS version Cy38r1 (2012), coupled atmosphere-land-ocean~~-~~-waves system	T159 ~125 km, 91 levels	1900-2010	4D-VAR
ERA-20CM	ECMWF	~~The~~ Ssimilar ~~model as~~to that used in ERA-20C (2012)	T159 ~125 km, 91 levels	1900-2010	3D-VAR
CERA-20C	ECMWF	IFS version Cy41r2 (2016), coupled atmosphere-ocean-land-waves-sea ice system	T159 ~125 km, 91 levels	1901-2010	CERA e~~E~~nsemble a~~A~~ssimilation technique
NOAA 20CRv2c	NOAA/ESRL PSD	NCEP GFS (2008), an updated version of the NCEP~~'s CFS,~~ Climate Forecast System (CFS) coupled atmosphere-land model	T62 ~210 km, 28 levels	1851-2014	Ensemble Kalman f~~F~~ilter
NOAA 20CRv2	NOAA/ESRL PSD	~~The s~~Same model as NOAA 20CRv2c (2008)	T62 ~210 km, 28 levels	1871-2012	Ensemble Kalman f~~F~~ilter
CFSR	NCEP	NCEP ~~Climate Forecast System (~~CFS~~)~~ (2011)~~,~~ coupled atmosphere-ocean-land-sea ice model	T382 ~38 km, 64 levels	1979-2010	3D-VAR

Table 1. Continued ~~at~~ from right column.

Related A~~A~~ssimilated and ~~/analyzed~~Analysed O~~O~~bservations	Sea I~~I~~ce and SSTs	GHG~~s~~ F~~f~~orcing	Reference
1) Includes~~d~~ ~~in-situ~~*in situ* observations of near-surface air temperature/pressure/relative humidity 2) Assimilates~~d~~ upper~~-~~air temperatures/wind/specific humidity 3) Assimilates~~d~~ rain-affected SSM/I radiances	A changing suite of SST and sea ice data from ~~the~~ observations and ~~the~~ NCEP	Interpolation by 1.6 ppmv/year from the global mean CO_2 in 1990 of 353 ppmv ~~of global mean CO2 in 1990~~	(Dee et al., 2011b)
1) ~~Analyzed~~Analyses available near-surface observations 2) Assimilates~~d~~ all available traditional and satellite observations	~~In-situ~~*In situ* observation-based estimates of the ~~the~~ COBE SST data and sea ice	~~The same as CMIP5~~Same as CMIP5	(Kobayashi et al., 2015)
1) Initiated with weather observations from ships, planes, station data, satellite observations and many more sources 2) No inclusion of near-surface air temperatures 3) Uses~~d~~ observed precipitation to nudge soil moisture 4) No information on aerosols	Reynolds SSTs for 1982 on and the ~~the~~ UKMO GISST data for earlier periods~~;~~; s~~S~~ea i~~I~~ce from SMMR/SSMI	Constant global mean CO_2~~CO2~~ of~~,~~ 330 ~~ppmv and no other~~ppmv; no other trace gases	(Kalnay et al., 1996)
1) No inclusion of near-surface air temperatures 2) No information on aerosols	AMIP-II prescribed	Constant global mean CO_2~~CO2~~, 350 ~~ppmv and no other~~ppmv; no other trace gases	(Kanamitsu et al., 2002)
1) Neither MERRA nor MERRA-2 ~~analyzed~~analyse near-surface air temperature, relative humidity ~~and so on~~, or other variables~~.~~ 2) ~~The r~~Radiosondes do provide some low~~-~~level observations~~.~~	Reynolds SSTs prescribed	~~The same as CMIP5~~Same as CMIP5	(Rienecker et al., 2011)
1) Includes~~d~~ newer observations (not included in MERRA) after the 2010s 2) Includes~~d~~ aerosols from MODIS and AERONET measurements over land after the 2000s and from the GOCART model before the 2000s 3) Assimilates~~d~~ observation-corrected precipitation to correct the model-generated precipitation before reaching the land surface	AMIP-II and Reynolds SSTs	~~The same as CMIP5~~Same as CMIP5	(Reichle et al., 2017)
1) Assimilates~~d~~ surface pressures from ISPDv3.2.6 and ICOADSv2.5.1~~,~~ and surface marine winds from ICOADSv2.5.1 2) Uses~~d~~ monthly climatology of aerosols from CMIP5	~~SST/sea-ice~~SSTs and sea ice from HadISST2.1.0.0	~~The same as CMIP5~~Same as CMIP5	(Poli et al., 2016)
Assimilates~~d~~ no data and includes~~d~~ radiative forcings from CMIP5	~~SST/sea-ice~~SSTs and sea ice realizations from HadISST2.1.0.0 used in 10 members	~~The same as CMIP5~~Same as CMIP5	(Hersbach et al., 2015)
1) Assimilates~~d~~ surface pressures from ISPDv3.2.6 and ICOADSv2.5.1~~,~~ and surface marine winds from ICOADSv2.5.1 2) Assimilates~~d~~ no data in the land, wave and sea ~~-~~ice components~~,~~ but uses~~d~~ the coupled model at each time step	SSTs from ~~the~~ HadISST2.1.0.0	~~The same as CMIP5~~Same as CMIP5	(Laloyaux et al., 2016)
Assimilates~~d~~ only surface pressure and sea level pressure	SSTs from HadISST1.1 and sea ice from ~~the~~ COBE SST ~~SST~~	Monthly 15 ° gridded ~~estimation~~ estimates of CO_2~~CO2~~ from WMO observations	(Compo et al., 2011)
~~The same~~Same as NOAA 20CRv2c	~~SST/sea-ice~~SSTs and sea ice from HadISST1.1	Monthly 15 ° gridded ~~estimation~~ estimates of CO_2~~CO2~~ from WMO observations	(Compo et al., 2011)
1) Assimilates~~d~~ all available conventional and satellite observations~~,~~ but not near-surface air temperatures 2) Atmospheric model contains~~ed~~ observed changes in aerosols 3) Uses~~d~~ observation-corrected precipitation to force the land surface analysis	G~~g~~enerated by coupled ocean-sea ice models~~,~~ ~~evolving~~; evolves freely during the 6-h coupled model integration	Monthly 15 ° gridded ~~estimation~~ estimates of CO_2~~CO2~~ from WMO observations	(Saha et al., 2010)

Table 2. Differences (unit: ℃) relative to the ~~homogenous~~ homogenized observations and t~~T~~rends (unit: ℃/decade) in surface air temperatures (T_a) from 1979 to 2010 over China and its seven subregions. The bold and italic bold fonts indicate results that are significant according to ~~a~~ two-tailed Student's *t*-tests with ~~a~~ significance levels of 0.05 and 0.1, respectively.

Regions	China		Tibetan Plateau		Northwest China		Loess Plateau		Middle China		Northeast China		North China Plain		Southeast China	
	Diff.	Trend	Diff.	Trend	Diff.	Trend	Diff.	Trend	Diff.	Trend	Diff.	Trend	Diff.	Trend	Diff.	Trend
ERA-Interim	-0.87	**0.38**	-3.49	**0.33**	-1.82	**0.37**	-0.32	**0.50**	-1.19	**0.28**	-0.03	**0.42**	-0.02	**0.45**	-0.03	**0.37**
NCEP-R1	-2.56	**0.23**	-6.80	0.11	-4.45	**0.39**	-1.77	**0.21**	-2.91	**0.23**	-1.28	**0.27**	-1.21	**0.23**	-1.33	**0.22**
MERRA	-0.48	**0.25**	-3.48	**0.33**	0.95	0.14	1.14	0.09	-1.35	**0.12**	-0.22	**0.52**	0.67	**0.26**	-0.27	**0.24**
JRA-55	-1.10	**0.38**	-3.49	**0.42**	-1.70	**0.39**	-0.58	**0.52**	-1.61	**0.30**	-0.25	**0.37**	-0.26	**0.41**	-0.50	**0.34**
NCEP-R2	-2.10	**0.25**	-5.76	-0.07	-4.29	**0.58**	-1.33	0.10	-2.80	**0.20**	-0.51	**0.36**	-0.38	**0.23**	-1.14	**0.36**
MERRA2	-0.91	**0.28**	-3.41	**0.35**	0.34	**0.32**	0.12	**0.19**	-1.35	**0.23**	-0.73	**0.41**	-0.24	0.18	-0.64	**0.25**
ERA-20C	-1.42	**0.29**	-6.56	**0.33**	-1.95	**0.31**	0.03	0.21	-2.01	**0.35**	-0.19	**0.32**	1.05	0.19	-0.47	**0.28**
ERA-20CM	-1.48	**0.32**	-5.93	**0.28**	-1.39	**0.38**	-0.36	**0.33**	-2.13	**0.27**	-0.23	**0.41**	-0.31	**0.34**	-0.51	**0.29**
CERA-20C	-2.06	**0.34**	-7.00	**0.41**	-2.15	**0.38**	-0.78	**0.36**	-2.59	**0.34**	-0.76	**0.43**	-0.40	0.19	-1.20	**0.29**
NOAA 20CRv2c	-0.28	**0.22**	-2.75	**0.39**	-0.01	**0.28**	1.62	0.16	-1.68	**0.18**	-0.16	0.11	1.06	0.15	0.18	**0.22**
NOAA 20CRv2	-0.32	**0.24**	-2.78	**0.33**	-0.01	**0.29**	1.48	0.20	-1.77	**0.19**	-0.07	0.25	0.97	0.21	0.12	**0.19**
CFSR	-1.74	**0.48**	-5.09	**0.46**	-1.03	**0.44**	-0.25	**0.40**	-2.91	**0.37**	-0.49	**0.67**	-0.37	**0.47**	-1.58	**0.51**
Obs-raw	0.03	**0.40**	0.03	**0.46**	0.09	**0.44**	0.01	**0.52**	0.05	**0.30**	0.00	**0.40**	0.05	**0.42**	0.03	**0.36**
Obs-homogenized		**0.37**		**0.44**		**0.36**		**0.50**		**0.24**		**0.41**		**0.38**		**0.33**

Table 3. Spatial pattern correlation (unit: 1) of three groups: partial relationships, trends and simulated ~~trend biases of~~biases in the trends in surface air temperature (T_a) against surface incident solar radiation (R_s), ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (PF) and surface downward longwave radiation (L_d). ~~The bold and italic bold fonts indicate a two-tailed Student's *t*-test with a significance level of 0.05 and 0.1, respectively.~~The bold and italic bold fonts indicate results that are significant according to two-tailed Student's t-tests with significance levels of 0.05 and 0.1, respectively.

Pattern Correlation	Partial Relationship						Trend				Trend Bias		
	(T_a, R_s)		(T_a, PF)		(T_a, L_d)		(T_a, T_a)	(T_a, R_s)	(T_a, PF)	(T_a, L_d)	(T_a, R_s)	(T_a, PF)	(T_a, L_d)
	Corr.	Slope	Corr.	Slope	Corr.	Slope							
ERA-Interim	**0.29**	0.01	0.03	**0.31**	**0.21**	**0.25**	**0.47**	**-0.11**	-0.04	**0.33**	**0.26**	**-0.12**	**0.10**
NCEP-R1	**0.30**	***0.06***	**0.18**	**0.30**	**0.36**	0.00	0.02	**-0.36**	-0.02	**0.62**	-0.03	-0.04	**0.43**
MERRA	**0.29**	0.06	**0.13**	**0.39**	0.05	**0.20**	**0.21**	**0.66**	**-0.81**	**-0.53**	**0.42**	**-0.62**	-0.05
JRA-55	**0.35**	**0.21**	**0.22**	**0.16**	**0.29**	**0.27**	**0.54**	**-0.33**	**0.31**	**0.57**	0.00	**0.14**	**0.29**
NCEP-R2	**0.22**	0.03	**0.20**	**0.36**	**0.27**	0.04	**-0.08**	**0.18**	**-0.29**	**0.28**	**0.15**	**-0.14**	**0.35**
MERRA2	**0.13**	0.05	**0.26**	**0.43**	**0.09**	**0.30**	**0.22**	**0.30**	**-0.11**	**0.11**	-0.02	**-0.12**	**0.28**
ERA-20C	**0.28**	***-0.07***	***-0.07***	**0.43**	**0.19**	0.02	-0.07	**0.18**	**-0.33**	0.03	**0.11**	**-0.25**	**0.31**
ERA-20CM	**0.24**	-0.04	-0.03	**0.32**	**0.26**	**0.18**	**0.28**	**-0.32**	**0.31**	**0.83**	-0.02	**0.12**	**0.34**
CERA-20C	**0.41**	**0.17**	**0.10**	**0.37**	**0.08**	***0.07***	**0.29**	**0.50**	**-0.58**	**-0.07**	-0.01	**-0.22**	**0.23**
NOAA 20CRv2c	**0.39**	**0.15**	**-0.22**	**0.25**	**0.14**	**0.15**	**0.08**	***-0.07***	**-0.11**	**0.55**	**-0.25**	***-0.05***	**0.50**
NOAA 20CRv2	**0.38**	**0.15**	**-0.21**	**0.18**	**0.14**	**0.23**	**0.19**	-0.02	**-0.20**	**0.56**	**-0.18**	**0.11**	**0.47**
CFSR	**0.33**	**0.12**	**0.10**	**0.19**	**0.37**	**0.21**	**0.19**	**0.11**	**-0.26**	**0.07**	**0.31**	**-0.08**	**0.15**
Obs-raw								***-0.07***	**0.27**	**0.50**			
Obs-homogenized								**-0.09**	**0.35**	**0.32**			

Figure Captions:

Figure 1. The multiyear-averaged differences in surface air temperatures (T_a, unit: ℃) during the ~~period 19~~period of 1979-2010 from the ~~twelve reanalysis~~twelve ~~product~~reanalysis products relative to the ~~homogeneous observation~~homogenized observations over China~~, i.e.,~~. The reanalysis products are (**a**) ERA-Interim, (**b**) NCEP-R1, (**c**) MERRA, (**d**) JRA-55, (**e**) NCEP-R2, (**f**) MERRA2, (**g**) ERA-20C, (**h**) ERA-20CM, (**i**) CERA-20C, (**j**) NOAA 20CRv2c, (**k**) NOAA 20CRv2 and (**l**) CFSR. The mainland of China is divided into seven regions (~~seen~~ shown in Fig. 1c), specifically ~~:~~ ① the Tibetan Plateau, ② Northwest China, ③ the Loess Plateau, ④ Middle China, ⑤ Northeast China, ⑥ the North China Plain and ⑦ South China.

Figure 2. The impact of ~~inconsistency~~ inconsistencies between station and model elevations on the simulated multiyear-averaged differences in surface air temperatures (T_a, unit: ℃) during the study ~~period 19~~period of 1979-2010 over China. The elevation difference (ΔHeight) between the stations and the models consists of the filtering error in the elevations used in the spectral model ~~elevations~~ (Δf) and the difference in site-to-grid elevations (Δs) due to ~~complex orography~~the complexity of orographic topography. ~~The~~ Δf is derived from the model elevations minus the 'true' elevations ~~at~~ in the ~~same model grid~~corresponding model grid cells from GTOPO30. The GTOPO30 orography is widely used in ~~the~~ reanalyses, e.g., by ECMWF. The ~~color~~colour bar denotes the station elevations (unit: m). The relationship of the T_a differences is regressed on ΔHeight (shown ~~in~~ at the bottom of each subfigure) or Δf and Δs (shown ~~in~~ at the top of each subfigure) ~~with~~; the corresponding explained

variances are shown.

Figure 3. Taylor diagrams for annual time series of the observed and re~~analyzed~~analysed surface air temperature anomalies (T_a, unit: ℃) from 1979 to 2010 in **(a)** China and **(b-h)** the seven subregions. The correlation coefficient, standard deviation and ~~root-mean-square~~ root mean squared error (RMSE) ~~were~~are calculated against the observed ~~homogeneous~~ homogenized T_a anomalies~~y~~.

Figure 4. Composite map of partial correlation coefficients of the detrended surface air temperature (T_a, unit: ℃) against surface incident solar radiation (R_s), ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (PF) and surface downward longwave radiation (L_d) during the ~~period 19~~period of 1979-2010 from observations and the ~~twelve reanalysis~~twelve ~~product~~reanalysis products. The marker '+' denotes the negative partial correlations of T_a with R_s over the Tibetan Plateau ~~for~~ in NCEP-R2, ERA-20C and ERA-20CM.

Figure 5. (**a**, **b**) The observed trends in surface air temperature (T_a, unit: ℃/decade) and the simulated ~~trend biases in~~biases in the trends in T_a~~,~~ (unit: ℃/decade) during the ~~period 19~~period of 1979-2010 from (**c**) raw observations and **(d-o)** the ~~twelve reanalysis~~twelve ~~product~~reanalysis products over China with respect to the ~~homogenous observation~~homogenized observations. The squares denote ~~from~~ the original homogeneous time series, and the dots denote~~s from~~ the adjusted homogeneous time series. The probability distribution functions of all of the biases in the trend~~ biases~~s are shown as ~~colored~~coloured histograms, and the black stairs are integrated from the trend biases with a significance level of 0.05 (based on two-tailed

Student's *t*-tests). The cyan and ~~/~~green sta~~i~~rs in (k-n) ~~are estimated~~represent estimates of the ~~trend biases~~ biases in the trends outside the ensemble ranges whose locations ~~is~~ are denoted~~s in~~ by the black dots shown in (k-n).

Figure 6. Composite map of the contributions (unit: ℃/decade) of the ~~trend biases in~~biases in the trends in three relevant parameters~~ [~~, surface incident solar radiation (R_s, in red), surface downward longwave radiation (L_d, in green) and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (in blue)~~]~~ to the ~~trend biases in~~biases in the trends in surface air temperature (T_a) during the study ~~period 19~~period of 1979-2010~~ from~~, as estimated using the ~~twelve reanalysis~~twelve ~~product~~reanalysis products over China.

Figure 7. Contribution s(unit: ℃/decade) of the ~~trend biases in~~biases in the trends in surface air temperatures (T_a) from three relevant parameters~~, i.e.,~~, surface incident solar radiation (R_s, in brown), surface downward longwave radiation (L_d, in light blue) and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (PF, in deep blue) during the study ~~period 19~~period of 1979-2010 from the ~~twelve reanalysis~~twelve ~~-product~~reanalysis products over China and its seven subregions.

Figure 8. Spatial associations of the simulated ~~trend biases in~~biases in the trend in surface air temperature (T_a) versus ~~relevant~~ three relevant parameters among the ~~twelve reanalysis~~twelve ~~-product~~reanalysis products (solid lines ~~for~~ indicate the NWP-like reanalyses, and dashed lines ~~for~~indicate the climate reanalyses). The probability density functions (unit: %) of these ~~trend biases~~biases in the trends ~~were~~are estimated from approximately 700 1°×1° ~~grids~~grid cells ~~over~~ that cover

China. ~~Median~~ The median values (~~colored~~coloured dots with error bars of spatial standard deviations) of the ~~trend biases in~~biases in the trends in T_a (unit: ℃/decade) in the twelve reanalyses ~~were~~are regressed onto those of (**a**) the surface incident solar radiation (R_s, unit: W m^{-2}/decade), (**b**) ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (unit: days/decade) and (**c**) the surface downward longwave radiation (L_d, unit: W m^{-2}/decade)~~,~~ using the ordinary least squares method (OLS, denoted by the dashed grey lines) and the weighted total least squares method (WTLS, denoted by the solid black lines). The 5-95% confidence intervals of the regressed slopes obtained ~~by the use of~~ using WTLS ~~were~~are shown as shading. The regressed correlations and slopes ~~were~~are shown as ~~as~~ grey and black ~~fonts~~text, respectively.

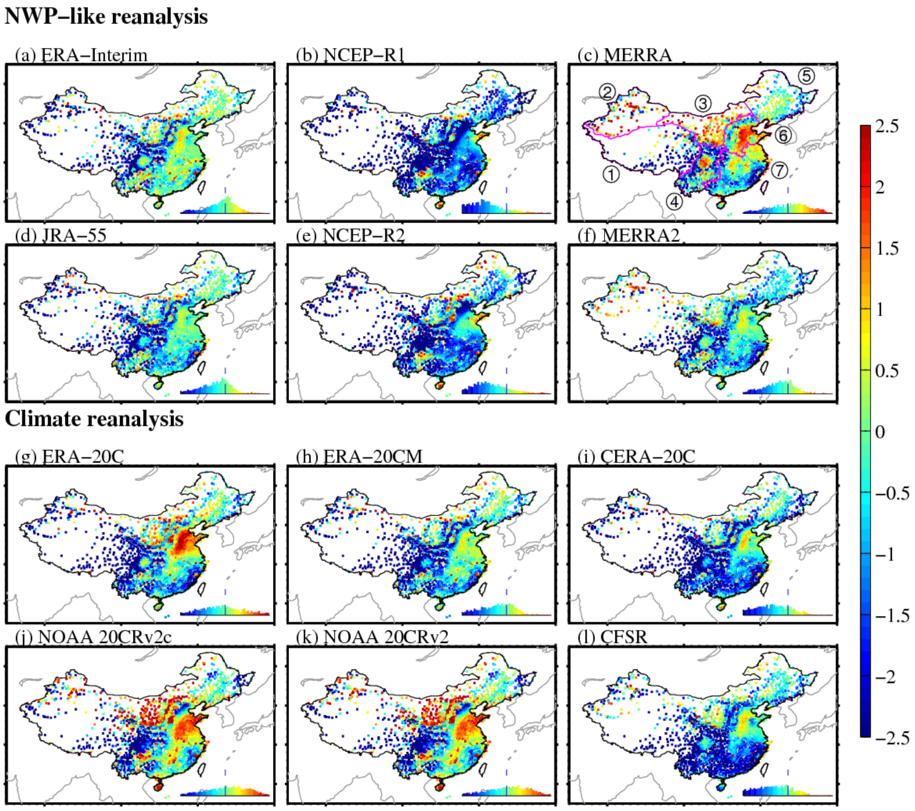

Figure 1. The multiyear-averaged differences in surface air temperatures (T_a, unit: ℃) during the ~~period 19~~period of 1979-2010 from the ~~twelve reanalysis~~twelve ~~product~~reanalysis products relative to the ~~homogeneous observation~~homogenized observations over China~~, i.e.,~~. The reanalysis products are (**a**) ERA-Interim, (**b**) NCEP-R1, (**c**) MERRA, (**d**) JRA-55, (**e**) NCEP-R2, (**f**) MERRA2, (**g**) ERA-20C, (**h**) ERA-20CM, (**i**) CERA-20C, (**j**) NOAA 20CRv2c, (**k**) NOAA 20CRv2 and (**l**) CFSR. The mainland of China is divided into seven regions (~~seen~~ shown in Fig. 1c), specifically ~~:~~ ① the Tibetan Plateau, ② Northwest China, ③ the Loess Plateau, ④ Middle China, ⑤ Northeast China, ⑥ the North China Plain and ⑦ South China.

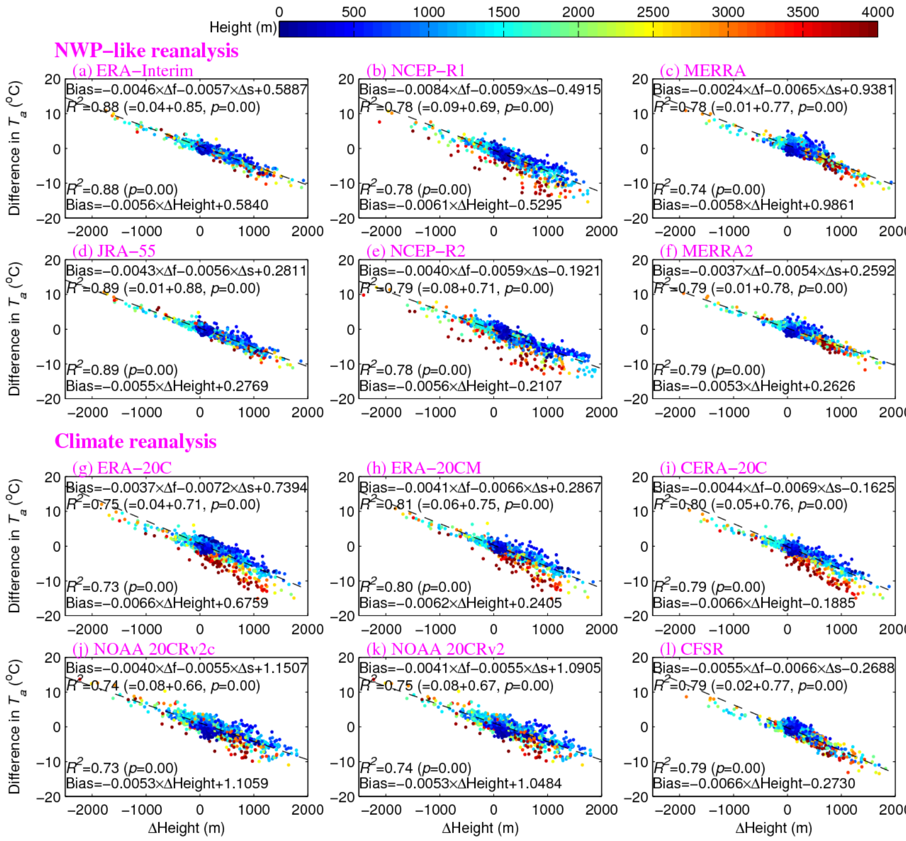

Figure 2. The impact of ~~inconsistency~~ inconsistencies between station and model elevations on the simulated multiyear-averaged differences in surface air temperatures (T_a, unit: ℃) during the study ~~period 19~~period of 1979-2010 over China. The elevation difference (ΔHeight) between the stations and the models consists of the filtering error in the elevations used in the spectral model~~ elevations~~ (Δf) and the difference in site-to-grid elevations (Δs) due to ~~complex orography~~the complexity of orographic topography.~~ The~~ Δf is derived from the model elevations minus the 'true' elevations ~~at~~ in the ~~same model grid~~corresponding model grid cells from GTOPO30. The GTOPO30 orography is widely used in ~~the~~ reanalyses, e.g., by ECMWF. The ~~color~~colour bar denotes the station elevations (unit: m). The relationship of the T_a

differences is regressed on ΔHeight (shown ~~in~~ at the bottom of each subfigure) or Δf and Δs (shown ~~in~~ at the top of each subfigure) ~~with~~; the corresponding explained variances are shown.

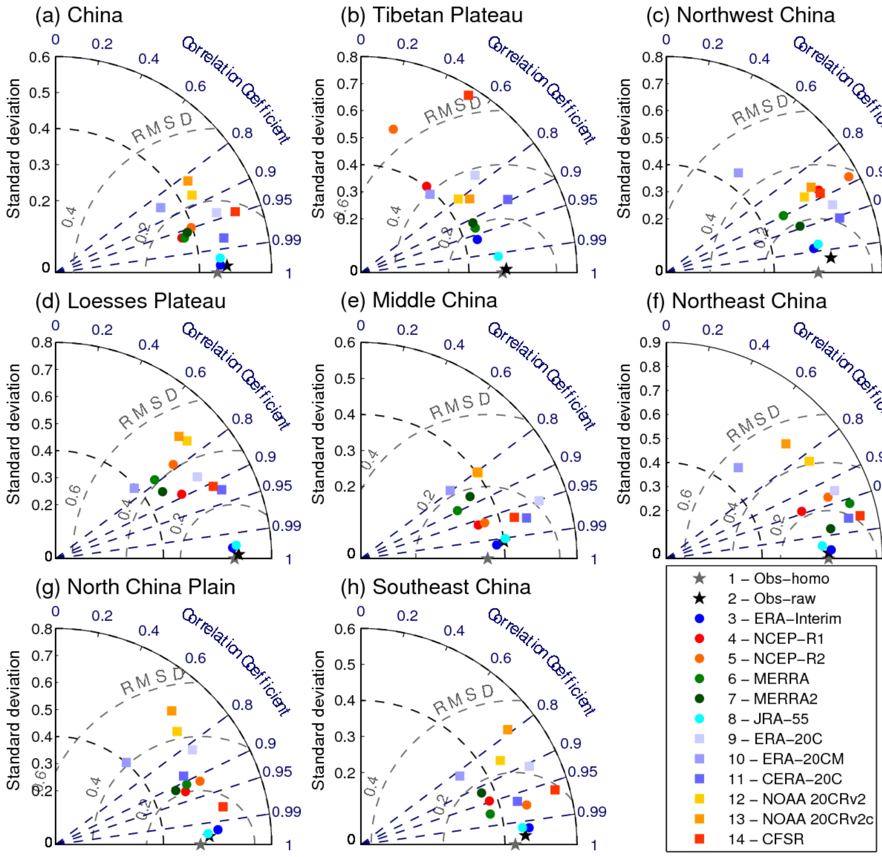

Figure 3. Taylor diagrams for annual time series of the observed and re~~analyzed~~analysed surface air temperature anomalies (T_a, unit: ℃) from 1979 to 2010 in **(a)** China and **(b-h)** the seven subregions. The correlation coefficient, standard deviation and ~~root-mean-square~~ root mean squared error (RMSE) ~~were~~are calculated against the observed ~~homogeneous~~ homogenized T_a anomal~~y~~ies.

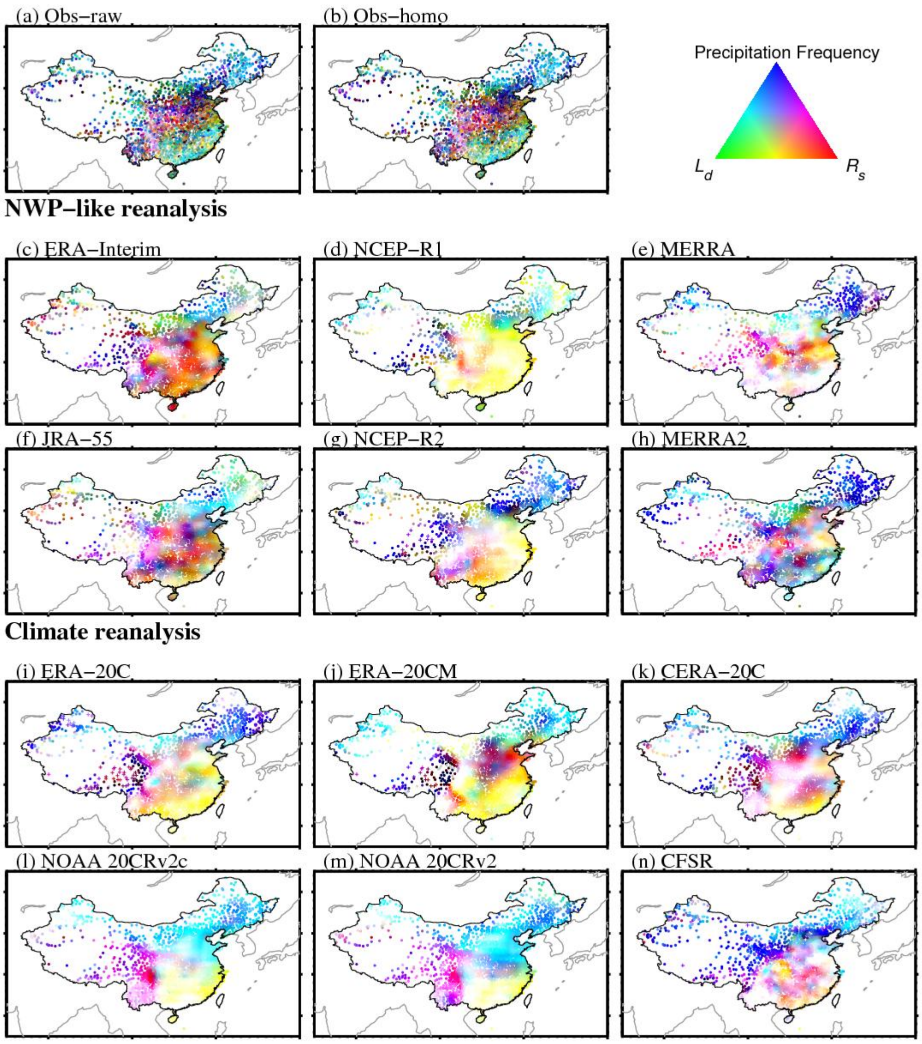

Figure 4. Composite map of partial correlation coefficients of the detrended surface air temperature (T_a, unit: ℃) against surface incident solar radiation (R_s), ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (PF) and surface downward longwave radiation (L_d) during the ~~period 19~~period of 1979-2010 from observations and the ~~twelve reanalysis~~twelve ~~-product~~reanalysis products. The marker '+' denotes the negative partial correlations of T_a with R_s over the Tibetan Plateau ~~for~~ in NCEP-R2, ERA-20C and ERA-20CM.

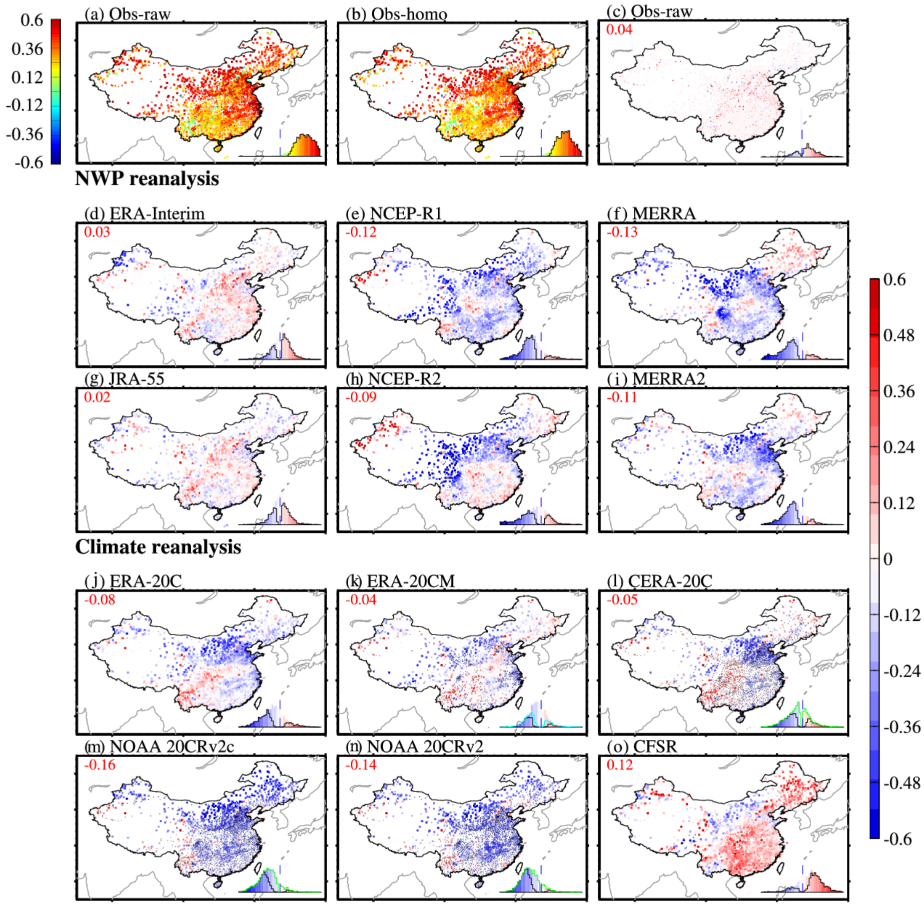

Figure 5. (**a**, **b**) The observed trends in surface air temperature (T_a, unit: ℃/decade) and the simulated ~~trend biases in~~biases in the trends in T_a~~,~~ (unit: ℃/decade) during the ~~period 19~~period of 1979-2010 from (**c**) raw observations and **(d-o)** the ~~twelve reanalysis~~twelve ~~-product~~reanalysis products over China with respect to the ~~homogenous observation~~homogenized observations. The squares denote ~~from~~ the original homogeneous time series, and the dots denote~~s from~~ the adjusted homogeneous time series. The probability distribution functions of all of the biases in the trend ~~biasess~~ are shown as ~~colored~~coloured histograms, and the black stairs are integrated from the trend biases with a significance level of 0.05 (based on two-tailed

Student's *t*-tests). The cyan and ~~/~~green sta~~i~~rs in (k-n) ~~are estimated~~represent estimates of the ~~trend biases~~ biases in the trends outside the ensemble ranges whose locations ~~is~~ are denoted~~s in~~ by the black dots shown in (k-n).

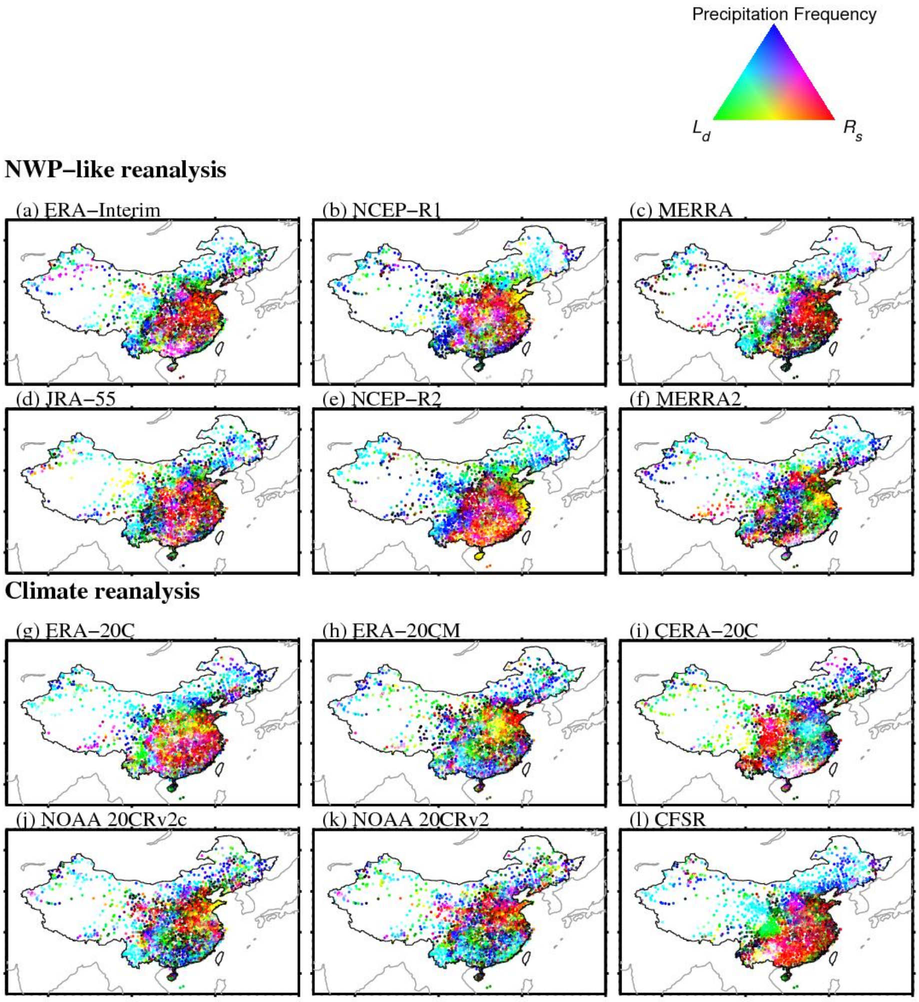

Figure 6. Composite map of the contributions (unit: ℃/decade) of the ~~trend biases in~~biases in the trends in three relevant parameters ~~[~~, surface incident solar radiation (R_s, in red), surface downward longwave radiation (L_d, in green) and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (in blue)~~]~~ to the ~~trend biases in~~biases in the trends in surface air temperature (T_a) during the study ~~period 19~~period of 1979-2010~~ from~~, as estimated using the ~~twelve reanalysis~~twelve ~~product~~reanalysis products over China.

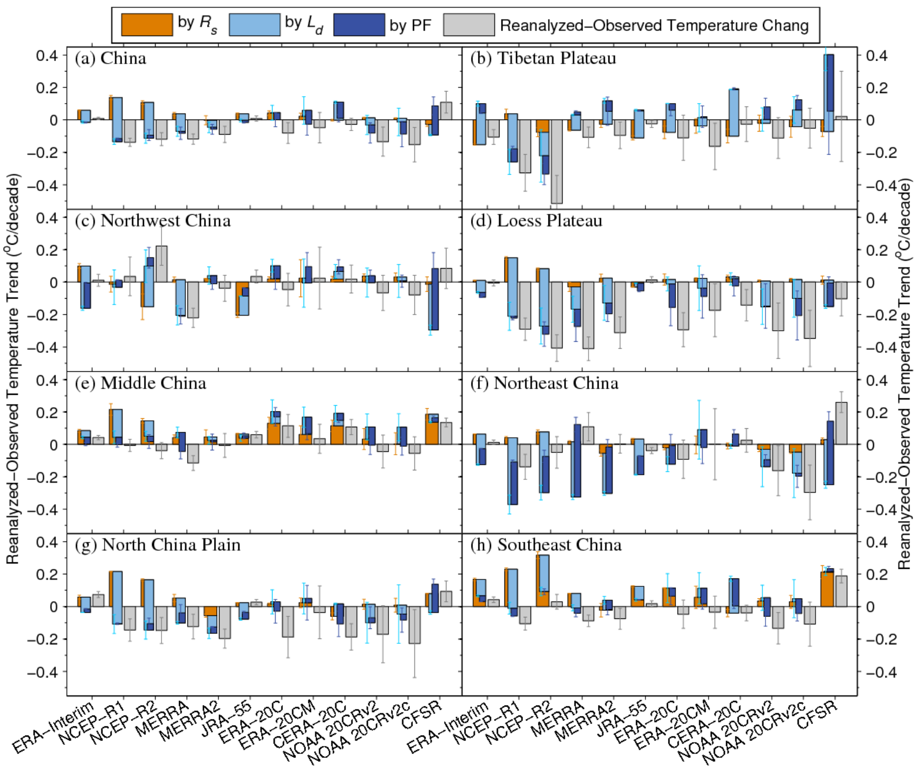

Figure 7. Contribution s(unit: ℃/decade) of the ~~trend biases in~~biases in the trends in surface air temperatures (T_a) from three relevant parameters~~, i.e.,~~, surface incident solar radiation (R_s, in brown), surface downward longwave radiation (L_d, in light blue) and ~~the precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (PF, in deep blue) during the study ~~period 19~~period of 1979-2010 from the ~~twelve reanalysis~~twelve ~~-product~~reanalysis products over China and its seven subregions.

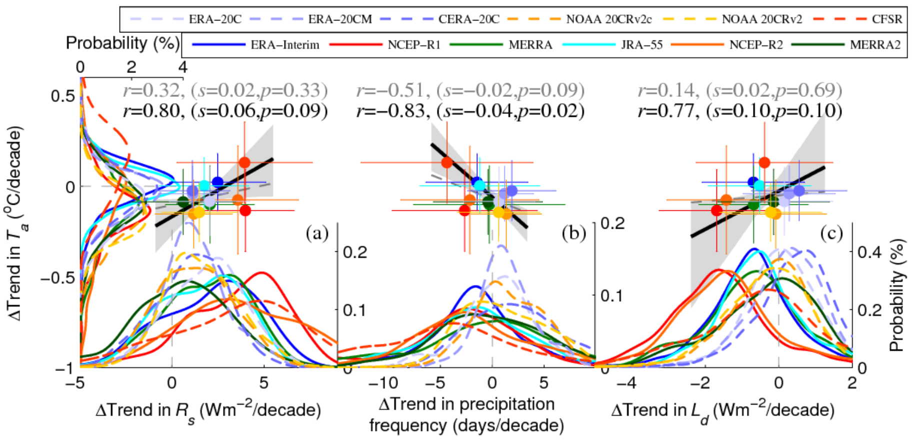

Figure 8. Spatial associations of the simulated ~~trend biases in~~biases in the trend in surface air temperature (T_a) versus ~~relevant~~ three relevant parameters among the ~~twelve reanalysis~~twelve ~~product~~reanalysis products (solid lines ~~for~~ indicate the NWP-like reanalyses, and dashed lines ~~for~~indicate the climate reanalyses). The probability density functions (unit: %) of these ~~trend biases~~biases in the trends ~~were~~are estimated from approximately 700 1°×1° ~~grids~~grid cells ~~over~~ that cover China. ~~Median~~ The median values (~~colored~~coloured dots with error bars of spatial standard deviations) of the ~~trend biases in~~biases in the trends in T_a (unit: ℃/decade) in the twelve reanalyses ~~were~~are regressed onto those of (**a**) the surface incident solar radiation (R_s, unit: W m^{-2}/decade), (**b**) ~~precipitation frequency~~~~the frequency of precipitation~~precipitation frequency (unit: days/decade) and (**c**) the surface downward longwave radiation (L_d, unit: W m^{-2}/decade)~~,~~ using the ordinary least squares method (OLS, denoted by the dashed grey lines) and the weighted total least squares method (WTLS, denoted by the solid black lines). The 5-95% confidence intervals of the regressed slopes obtained ~~by the use of~~ using WTLS ~~were~~are shown as shading. The

regressed correlations and slopes ~~were~~are shown as ~~as~~ grey and black ~~fonts~~text, respectively.