Reviewer1:

Thank you very much for your support and generous comments. Please find below the response and respective modifications in the manuscript (shown in the quotation mark).

Summary: the authors examine two different ways to estimate drought recovery: a storage deficit approach, in which GRACE TWSA is used to define the end of a drought, and a required precipitation approach that tracks (or forecasts) cumulative rainfall deficit. They conclude that there is good agreement between the two methods in most regions that satisfy tests of moderate or strong rainfall-storage coupling. Bringing these two methods together is both interesting and potentially valuable in the context of forecasts–presumably, for regions in which this analysis approach works well, a skillful precipitation forecast could be used to predict the cessation of TWSA drought up to several months in advance. Of course, this hinges on having such a skillful precipitation forecast, but the framework presented here provides a guide to how the prediction would be implemented. I believe that the discussion paper can be accepted as a final HESS paper after moderate revision. My specific comments are listed below. I am particularly interested in the authors' response to comment #7, as I fear that I am missing some key element of their methodology. If I'm not missing something then I would recommend that the authors reframe or remove the forecast materials that led me to make that comment.
Response: We really appreciate the supportive and positive comments from the reviewer.

Specific comments:

1. line 18: what is "simplistic precipitation forecast skill"? I think some rephrasing is required.

Author's response: We rephrased it to "simplistic precipitation forecast skill based on the integration of climatology and long-term trend." (line 21)

2. Introduction: as stated in my summary, my understanding is that this study is motivated by (or, at least, could be motivated by) the problem of monitoring and forecasting the end of a drought on the basis of precipitation requirements. But it took me a while to come to that understanding, in part because the introduction does not, in my opinion, offer a clear statement of the intellectual contribution of this paper. There is good material reviewing GRACE and reviewing drought cessation estimates, but the final paragraph of the introduction simply states what the authors are going to do and not why they are doing it in the context of a gap in the literature or a target application. It would be helpful to have a few sentences that make the importance of this paper clearer.

Author's Response: Thanks, we added a line as advised. "The intellectual contribution of this paper is in the estimation drought recovery and conceptually bringing a framework for drought recovery forecast based on precipitation deficit." (line 110) . Additionally, we rearranged the paragraph to make it clearer.

3. GRACE data: how sensitive are these results to the choice of GRACE product? If only mascon are to be used then please justify the choice of mascon over spherical harmonics solutions for this application. Also, more than one mascon solution is now available, and

> it would be useful to see that the results presented here are robust to the choice of mascon product.

Author's response: We understand the reviewer's concern about the possible discrepancies between different GRACE solutions, as they are produced using different approaches by different centers. We added a couple of lines in the GRACE section and added a supplementary material comparing different GRACE solution for an example location. In this study we used JPL based mascon GRACE solution as it has a relatively similar spatial resolution (3°x 3°) as that of GPCP (2.5°x 2.5°). We have also acknowledged that though GRACE mascon and GPCP 2.5 degree is considered as comparable, nevertheless areas of the unit representations are different at different locations
Following lines are added in the section 2.1

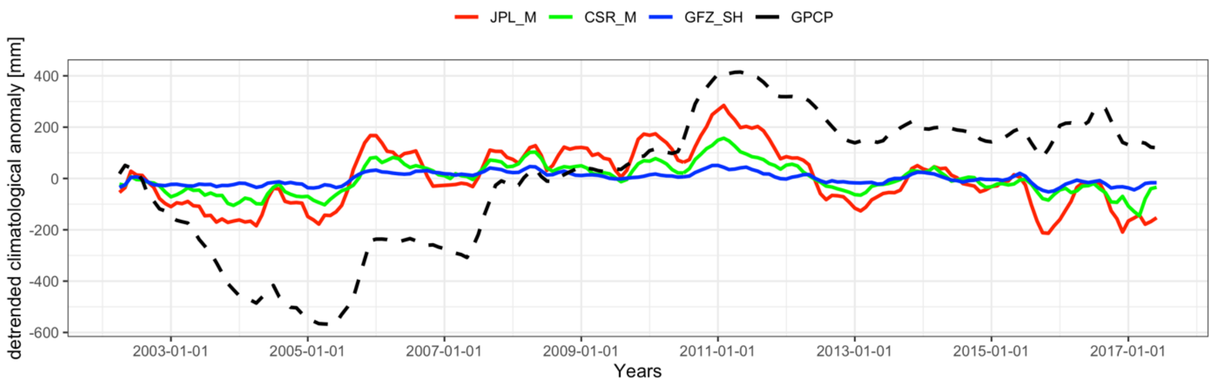
"The GRACE level-3 solution is officially available from three different centers, which are produced using different approaches (spherical harmonics or mascon), different filers, smoothing factors, etc. and eventually, there can be discrepancies between different TWS estimates from GRACE solutions (Jing et al., 2019). The differences between GRACE solutions from different centers are mostly very small at a basin level and lie within the error bounds of the GRACE solution itself (Sakumura et al., 2014). However, at 0.5-degree grid the difference between the amount of missing water estimated by the different GRACE solutions increases substantially (as seen in the supplementary material). This caveat can be mitigated in future by using ensemble of GARCE products. Nevertheless, they are consistent with the detection of drought duration. Please look into the supplementary material for the comparison between water storage deficit estimated by the different GRACE solutions.

Supplementary material

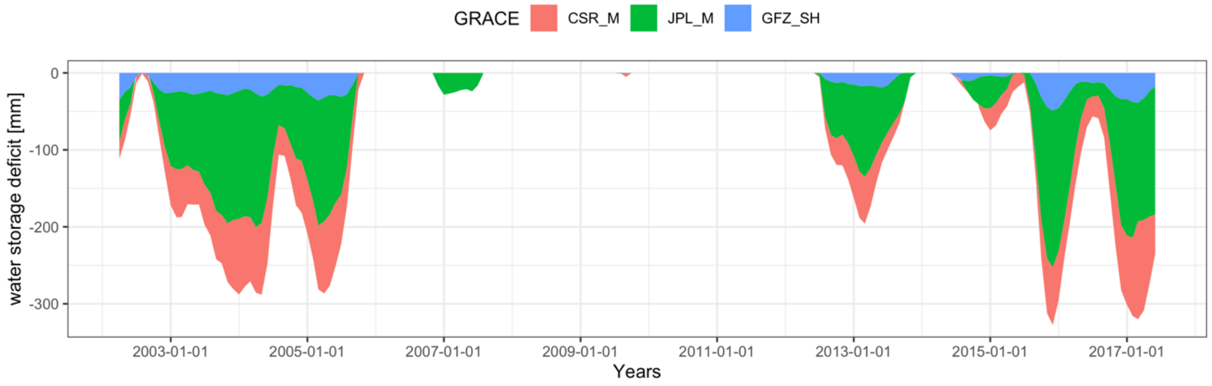
The official GRACE Science Data System continuously released monthly GRACE solution for three different processing centers: GeoforschungsZentrum Potsdam (GFZ), Center for Space Research at University of Texas, Austin (CSR), and Jet Propulsion Laboratory (JPL). These three solutions used different parameters and strategies, such as different degree and order, spherical harmonic coefficient, spatial filter and smoothing factor (Jing et al., 2019). The JPL mascon (JPL-M) and CSR mascon (CSR-M) solutions were provided at 0.5 degrees at https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/ and http://www2.csr.utexas.edu/grace/RL05_mascons.html respectively. GFZ produces only spherical harmonic solution (GFZ-SH), which is downloaded from http://isdc.gfz-potsdam.de/grace-isdc/.
Figure11 shows water storage deficit and estimated required extra precipitation to overcome the drought based on three different GRACE solutions, using the method described in the article for an example location in India (centered on 77.25°E 15.25°N). Sakumura et al., 2014 demonstrated that at a basin-scale, the differences between them are very less. However, the plot shows that there are discrepancies between the amount of missing water at 0.5degree grid because every center has a different method to downscale GRACE inherent spatial resolution to high-resolution grid. Figure 11a shows the detrended climatological anomaly of the three GRACE solutions and cumulative GPCP precipitation has similar variability. The negative anomaly from climatology is

considered as drought and is plotted in figure11b. It shows that the difference between CSR and JPL solutions are relatively less than GFZ solution because the first two are the mascon-based solution and are available at 0.5-degree grid (after scaling), while GFZ solution is spherical harmonics based and is re-gridded to 0.5 degree from 1-degree spatial resolution by simple bilinear interpolation. Based on the linear relationship between cumulative detrended GPCP anomaly and detrended GRACE anomalies, required extra precipitation is estimated (figure 11c). The figure shows that the required precipitation varies based on GRACE solutions. Nevertheless, all three GRACE solutions are consistent with the detection of drought duration.

a.



b.



c.

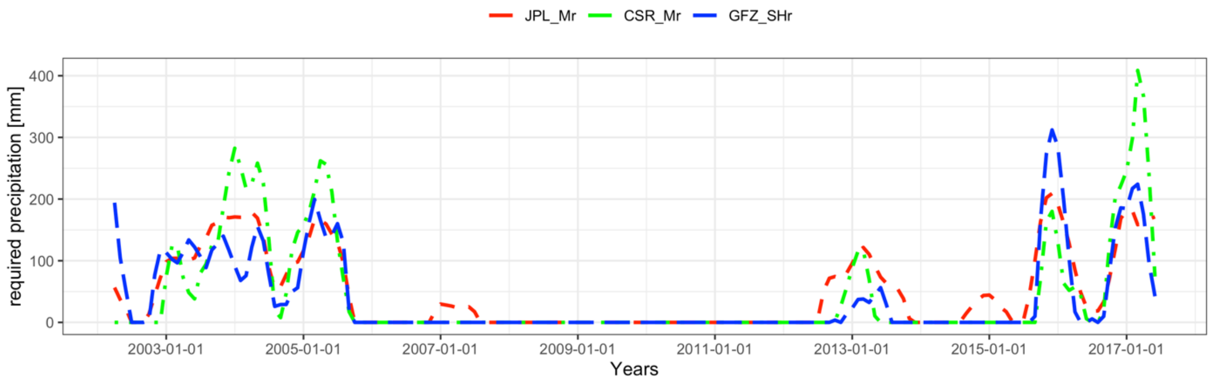


Figure 11: Water storage deficit and estimated required precipitation based on the spherical harmonic solution from GFZ and the mascon solutions from CSR and JPL .a. Cumulative detrended precipitation anomaly (cdPA) compared with the detrended storage anomaly (dTWSA). b) The negative residuals from the GRACE climatology considered as drought. c) Surplus required-precipitation is estimated based on the linear relationship between dTWSA and cdPA, to fill the storage deficit (middle panel)).

Jing, W., Zhang, P. and Zhao, X.: A comparison of different GRACE solutions in terrestrial water storage trend estimation over Tibetan Plateau, Sci Rep, 9, doi:10.1038/s41598-018-38337-1, 2019.
Sakumura, C., Bettadpur, S. and Bruinsma, S.: Ensemble prediction and intercomparison analysis of GRACE time-variable gravity field models, Geophysical Research Letters, 41(5), 1389–1397, doi:10.1002/2013GL058632, 2014.

4. GPCP: similar question here. How sensitive is the analysis to choice of precipitation dataset? There are a number of choices available for the period of study.

Author's response: Yes, we agree, there are many precipitation products like CRU, GPCC, etc. However, GPCP is a widely used global precipitation data. GPCP combines the strength offered by in situ as well as satellite data. In many regions of the world in situ data are sparse, so using a product that only utilizes in situ data may not be the best choice. GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al. 2018). Besides, in section 3.3 historical analysis of the data is done using 1979-2017 precipitation data. For this period GPCP is the best available data.

Following sentences are added in the GPCP section
"Global Precipitation Climatology Project (GPCP) is a widely used global precipitation data. Most of the other observational products don't produce precipitation estimates beyond 60deg S/N for longer historical period (1979 – present). Besides, GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al., 2018)
Behrangi, A., A. Gardner, J. T. Reager, J. B. Fisher, D. Yang, G. J. Huffman, and R. F. Adler (2018), Using GRACE to Estimate Snowfall Accumulation and Assess Gauge Under catch Corrections in High Latitudes, Journal of Climate, 31(21), 8689-8704, doi: 10.1175/jcli-d-18-0163.1."

5. line 110 et seq.: It is true that a long-term linear trend is often due to non-climatic processes. But some GRACE trends ARE due to climate–for example, a major drought at the beginning or end of the record. The authors should comment on this possibility at some point in the manuscript, and discuss its implications for results in some regions.

Author's response: Thanks for bringing in, we added a line: "We acknowledge the caveat of a possibility of sudo-trend due to unusual signal at the beginning or end of the record in some regions."

6. line 158 et seq.: "Figure 2" in this passage is actually Figure 3.

Author's response: The maps in Figure 2 demonstrate the strength of the TWA precipitation relationship globally. So, Figure 2 is correct.

7. Section 3.3.2 and other materials on forecasts: I have to admit that I don't understand the emphasis on these hindcasts in the paper. As the authors acknowledge, it's a simple method that doesn't provide very meaningful forecasts. So what is it used for? It seems that the analysis presented in the results section only requires statistics of historical rainfall (mean and standard deviations) that can be compared to observation. The forecasts simply seem to play the role of a not-quite-perfect estimate of climatology. I do understand the authors' point about why forecasts might be useful in the context of predicting the end of drought via forecast of required precipitation. But there is no demonstration of this value in the current paper, as far as I can tell; there's only the claim that it might be valuable.

Author's response: The signal reconstruction and forecast discussed in section 3.3.2 is essential as we used it to create a normal signal first and then used standard deviation to simulate two additional precipitation scenarios of wet and extremely wet conditions. The normal signal is composed of predominantly climatology and long-term trend as the demonstrated model has the least competence in the estimation of inter-annual signals (0-3months). These precipitation scenarios are further needed to demonstrate the possible recovery duration from drought. Nevertheless, it is a very simplistic forecast and we agree with the reviewer that it can be further simplified by using mean and standard deviation. The idea here is to demonstrate that given the three possible scenarios of precipitation, we can estimate the recovery period because by using the GRACE-precipitation relationship we know how much is the required precipitation.

8. line 254: Doesn't blue n this figure indicate good agreement??

Author's response: That's right, thanks. But colors are modified to the sequential lightness-hue ramp as per the other reviewer's comments.

9. line 269 et seq.: It appears that Figure 10 is incorrectly referred to as Figure 8 throughout this passage.

Author's response: That's right, thanks, we corrected it.

10 Section 4.2.2: I assume that Figure 10 here really refers to Figure 11

Author's response: That's right, thanks for pointing out. Figures are modified and their numbers are corrected.

I recommend an edit for style and grammar. The paper is clear, but there is some awkward phrasing.

Author's response: Edited the manuscript. Many thanks for the supportive comments

Reviewer 2

We are highly thankful for the detailed and supportive comments provided by the reviewer. Please find the response below. Modifications in the manuscript are shown within quotation marks.

Summary:

The presented work shows an integrated precipitation approach to determine the recovery period and required precipitation to refill water storages and thus to overcome a hydrological drought. Thus, historical integrated precipitation is linked to total water storage anomalies (TWSA) by GRACE to combine and validate their precipitation- based methodology to an existing storage deficit methodology. Furthermore, three scenarios of precipitation forecast are provided to identify the best estimated time of recovery. They found that the recovery period of integrated precipitation is in good agreement with the recovery period from TWSA, especially in regions where integrated precipitation and total water storage changes showed a strong linear relationship. I think that this work discusses an important topic to have a better understanding of drought evolution and to use this information possibly in water management. The methodology and findings are of good scientific quality and significance, but yet I have general and specific concerns, especially regarding to presentation quality, that are listed below. Thus, I recommend major revision, but believe that the manuscript could be published after addressing/clarifying my comments.

Response: We agree and appreciate the reviewer for guiding the paper in such a detail to improve its clarity and focus.

General comments

1. Until the first results were shown, it was not clear if the precipitation or the GRACE approach is the main contribution of the paper. This is important for abstract, introduction, conclusion and maybe should also be more consistent with the title and structure of the data and methods chapter. For example, [Page1 Line14] says the main goal is the combination of GRACE and precipitation, while [Page1 Line21] let assume that the author's main point is the precipitation approach and GRACE is only used as validation.

Author's response: We thank the reviewer for bringing this up. The paper uses both GRACE and GPCP equally, therefore, the title is modified as 'Estimation of hydrological drought recovery based on precipitation and GRACE water storage deficit'. GRACE is also used for validation but the main focus of this work is drought recovery estimation, based on the required precipitation, which is estimated from GRACE ad precipitation dataset. Added a line "The intellectual contribution of this paper is in the estimation drought recovery and conceptually bringing a framework for drought recovery forecast based on precipitation deficit. " (line 109)

2. More clarification is needed about the drought definitions. Do you place your approach more in the context of hydrological drought or drought in general? The manuscript should be consistent according to the drought definitions. Be also clear about other drought categories of parameters, e.g.: [Page 1 Line32] meteorological drought is not only described by precipitation, also evapotranspiration. [Page1 Line34] soil moisture, precipitation, and runoff and not all hydrological parameters. For exam- ple, precipitation is a meteorological parameter.

Author's response: A sentence is modified in the introduction to clarify that the study is more in the context of hydrological drought. ' This study focusses on hydrological drought, which requires, combining both surface (snow and surface water), and subsurface (soil moisture and groundwater) hydrological information.' (line 43)

drought categories of parameters are modified:

"including agricultural (soil moisture deficit), meteorological (eg. precipitation deficit or increase in evapotranspiration), and hydrological (storage deficit for eg. in streamflow/groundwater) droughts." (line 40)

3. Why are mascons used instead of spherical harmonics, the mascon solutions are underlying by constraints. Does the cap size of 3 x 3 degree of mascon solution then not represent a similar spatial resolution as the spherical harmonic GRACE resolution?

Author's response:
We understand the reviewer's concern about the possible discrepancies between different GRACE solutions, as they are produced using different approaches by different centers. Mascon based GRACE solution has less leakage of signals than spherical harmonic solution and do not necessitate empirical filters to remove north-south stripes. Therefore, spatial resolution of 3x3 mascon is a bit different than spherical harmonics. We added a couple of lines in the GRACE section and added a supplementary material comparing different GRACE solution for an example location. In this study we used JPL based mascon GRACE solution as it has a relatively similar spatial resolution (3°x 3°) as that of GPCP (2.5°x 2.5°). We have also acknowledged that though GRACE mascon and GPCP 2.5 degree is considered as comparable, nevertheless areas of the unit representations are different at different locations. Following lines are added in the section 2.1

"The GRACE level-3 solution is available from different centers are produced using different approaches (spherical harmonics or mascon), different filers, smoothing factors, etc. and eventually, there can be discrepancies between different TWS estimates from GRACE solutions (Jing et al., 2019). The differences between GRACE solutions from different centers are mostly very small at a basin level and lie within the error bounds of the GRACE solution itself

(Sakumura et al., 2014). However, at 0.5-degree grid the difference between the amount of missing water estimated by the different GRACE solutions increases substantially (as seen in the supplementary material). This caveat can be mitigated in future by using ensemble of GARCE products. Nevertheless, they are consistent with the detection of drought duration. Please look into the supplementary material for the comparison between water storage deficit estimated by the different GRACE solutions.

In the conclusion section following lines are added
'However, careful cautions are warranted to interpret the GRACE signal at 0.5 degree grid due to different post processing techniques applied by different GRACE solutions to overcome the inherent limitation in the spatial resolution of GRACE.
Significant ant difference in intensity of drought is observed by different GRACE solutions. Nevertheless, all GRACE solutions have same drought duration.'

Supplementary material

The official GRACE Science Data System continuously released monthly GRACE solution for three different processing centers: GeoforschungsZentrum Potsdam (GFZ), Center for Space Research at University of Texas, Austin (CSR), and Jet Propulsion Laboratory (JPL). These three solutions used different parameters and strategies, such as different degree and order, spherical harmonic coefficient, spatial filter and smoothing factor (Jing et al., 2019). The JPL mascon (JPL-M) and CSR mascon (CSR-M) solutions were provided at 0.5 degrees at https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/ and http://www2.csr.utexas.edu/grace/RL05_mascons.html respectively. GFZ produces only spherical harmonic solution (GFZ-SH), which is downloaded from http://isdc.gfz-potsdam.de/grace-isdc/.

Figure11 shows water storage deficit and estimated required extra precipitation to overcome the drought based on three different GRACE solutions, using the method described in the article for an example location in India (centered on 77.25°E 15.25°N). Sakumura et al., 2014 demonstrated that at a basin-scale, the differences between them are very less. However, the plot shows that there are discrepancies between the amount of missing water at 0.5degree grid because every center has a different method to downscale GRACE inherent spatial resolution to high-resolution grid. Figure 11a shows the detrended climatological anomaly of the three GRACE solutions and cumulative GPCP precipitation has similar variability. The negative anomaly from climatology is considered as drought and is plotted in figure11b. It shows that the difference between CSR and JPL solutions are relatively less than GFZ solution because the first two are the mascon-based solution and are available at 0.5-degree grid (after scaling), while GFZ solution is spherical harmonics based and is re-gridded to 0.5 degree from 1-degree spatial resolution by simple bilinear interpolation. Based on the linear relationship between cumulative detrended GPCP anomaly and detrended GRACE anomalies, required extra precipitation is estimated (figure 11c). The figure shows that the required precipitation varies based on GRACE solutions. Nevertheless, all three GRACE solutions are consistent with the detection of drought duration.

Figure 21: Water storage deficit and estimated required precipitation based on the spherical harmonic solution from GFZ and the mascon solutions from CSR and JPL .a. Cumulative detrended precipitation anomaly (cdPA) compared with the detrended storage anomaly (dTWSA). b) The negative residuals from the GRACE climatology considered as drought. c) Surplus required-precipitation is estimated based on the linear relationship between dTWSA and cdPA, to fill the storage deficit (middle panel)).

Jing, W., Zhang, P. and Zhao, X.: A comparison of different GRACE solutions in terrestrial water storage trend estimation over Tibetan Plateau, Sci Rep, 9, doi:10.1038/s41598-018-38337-1, 2019.
Sakumura, C., Bettadpur, S. and Bruinsma, S.: Ensemble prediction and intercomparison analysis of GRACE time-variable gravity field models, Geophysical Research Letters, 41(5), 1389–1397, doi:10.1002/2013GL058632, 2014.
.

4. [Page3 Line103] Which method is used to regrid the data? Is there a precipitation data set with an 0.5 degree resolution? I ask myself if the downscaling from 2.5 to 0.5 degree has a significant impact.

Author's response: GPCP is a widely used global precipitation data. In section 3.3 historical analysis 1979-2017 of the precipitation data is done. For this period GPCP 2.5degree is the best available data which is interpolated to 0.5 degree by using the bilinear method to harmonize it with the GRACE grid. There are many higher resolution precipitation products like TRMM, CRU, GPCC, etc. However GPCP combines the strength offered by in situ as well as satellite data to obtain global picture while others are limited to 60 degrees North and South latitudes. Additionally, GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al. 2018). Besides, in section 3.3 historical analysis of the data is done using 1979-2017 precipitation data. For this period GPCP is the best available data. We also acknowledge the caveat of different re-gridding method in GRACE and GPCP.
Following sentences added in the GPCP section:
"Global Precipitation Climatology Project (GPCP) is a widely used global precipitation data. Most of the other observational products don't produce precipitation estimates beyond 60deg S/N for longer historical period (1979 – present). Besides, GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement. (Behrangi et al., 2018)

Nevertheless, areas of the unit representations are different in tens of thousands km^2 at different locations which get worst towards pole. We also acknowledge the possible caveat due to different methods of re-gridding of both the datasets, which can be improved in future work. However, as drought is a smooth process the impact of neighboring pixels should not affect the analysis significantly.

Behrangi, A., A. Gardner, J. T. Reager, J. B. Fisher, D. Yang, G. J. Huffman, and R. F. Adler (2018), Using GRACE to Estimate Snowfall Accumulation and Assess Gauge Under catch Corrections in High Latitudes, Journal of Climate, 31(21), 8689-8704, doi: 10.1175/jcli-d-18-0163.1.

5. [Page3 Line110] Why are the TWSA smoothed with an averaging filter? Does their noise have a significant impact on the results?

Author's response: As drought develops in a smooth progression and we are looking for the amount of missing mass in a system caused by drought. Therefore, 3months moving average is considered as a better representation of the progression of drought. Monthly observations also have similar relationship between TWS and precipitation but signals are neat and better interpretable after averaging filter.

6. [Page4 Line129-136] The linkage between integrated precipitation and GRACE is an important aspect for the validation so it should be explained more detailed. The paragraph is (probably) based on the water balance equation, which should at least be mentioned but better also shown. The assumptions that were decided to describe the relationship about evapotranspiration/runoff should be added here and it also should get clear how the precipitation is integrated in time. So for example, is it integrated continuously for each month to the previous months or is there an integration period of 3 months that is running over all months etc.?

Author's response: We understand the reviewer’s point and added the following lines in section 3.2:

$$dS/dt = P - ET - R \qquad \text{Eq. 1}$$

“

The water balance equation based on hydrological fluxes (Eq. 1) shows that the change in terrestrial water storage (dS) in a region for a given month (dt) depends on the monthly precipitation (P, mm/month); evapotranspiration (ET, mm/month) and the streamflow (R, which includes both surface water and subsurface water) (Swenson and Wahr, 2006). Assuming the relationship between precipitation and ET + R remains constant for a region, the variability in precipitation gives an idea of possible variation in the storage

Swenson, S. and Wahr, J.: Estimating Large-Scale Precipitation Minus Evapotranspi- ration from GRACE Satellite Gravity Measurements, J. Hydrometeor., 7(2), 252–270, doi:10.1175/JHM478.1, 2006. “ (line181)

7. [Page4 Lines144-147 and Lines158-162] It was not clear how the required precipita- tion is linked to the regression coefficients. It would great if the linkage for the example of a coefficient lower/higher/equal 1 in the first paragraph is clearly explained. Sec- ondly, how do we then get the surplus required-precipitation? Is it derived by removing cdPA from dTWSA?

Author's response: It is a great idea; we added a small description in section 3.2:

“Based on the linear relationship between dTWSA and cdPA the required precipitation has been estimated. Regression coefficients greater than 1 means the required precipitation is more than the amount of missing water. This is because precipitation lost in other hydrological processes like evapotranspiration, runoff (Eq.1) is not observed by storage variability). Coefficient equals to 1 means the amount of required precipitation is the same as that storage loss, which means there is no other dominant process in the region. Coefficient less than 1 are the regions of weak precipitation-storage coupling, which can be due to other physical processes like melting of snow/frozen surfaces, groundwater extraction, irrigation, etc (non-red regions in Figure 2a).” (line 210)

Figure 4, as well as some other figures, is analyzed too shortly (e.g. [Page5 Line181]) or, for example, only part a) of a), and b) is described. The figures provide much more information, especially about spatial differences. So, the figures should be described more in detail, which I prefer because they contain interesting findings, or removed/added to supplementary.

Author's response: We agree with the reviewer’s point and added small description of the figure.

“Figure 4 shows the fractional variance of the decomposed signal. For most regions, annual signal dominate in precipitation (Figure 4a). However, regions where the wet season is not explicit in their climatology, high-frequency signal plays a major role, for example in central Europe, eastern Siberia, western N. America, southern Australia, etc. (Figure 4c). Contrarily, the long-term signal obtained by combining linear trend and the inter-annual signal has the least variability globally (Figure 4b). These smooth signals are driven by climate indices like El Niño southern oscillation (ENSO), Pacific decadal oscillation (PDO), and the North Pacific mode (NPM), etc. (Özger et al., 2009). The annual and long-term signals are directly applied for the signal reconstruction with the assumption that a similar trend will continue. “

Özger, M., Mishra, A. K. and Singh, V. P.: Low-frequency drought variability associated with climate indices, Journal of Hydrology, 364(1), 152–162, doi:10.1016/j.jhydrol.2008.10.018, 2009” (line 260)

8. [Page5 Line188] It is not clear how the sub-seasonal signal is computed and where the number of 0 to 3 months of reconstruction is resulting from. The final hindcast is 2 years, so how did the authors manage the 0-3 months restriction of the sub-seasonal signal?

Author's response: A sentence is added in section 3.3.2

“The sub-seasonal signal is obtained from the residual of the inter-annual signal. This high frequency signal has 0-3 months of temporal autocorrelation; accordingly, we have limited skill in synthesizing sub-seasonal signal.” (line 295)

9. [Page7 Line247] The definition of severe drought was not exactly set. What is the definition or to which definition is it referred?

Author's response: A line added

“Here, the severity of a drought defined by the amount of water shortage in a month.” (line 348)

[Page7 Line253] Based on which principles are the differences of recovery months divided into the different classes? How were the classes determined? It leads also to confusion in Figure 9. Without reading the caption it seems as if the difference is very small everywhere (from 1 to 4 months), but the number does not represent the "difference in months", rather the "class number of differences in months".

Author's response: Label of the figure is modified (thanks for pointing). The first two classes are defined by 2 months difference, as majority of regions have less difference than the third class has 4 months difference and last class is has no upper limit.

10. [Page9 Line333] Could you please discuss that the recovery period derived from precipitation is also underlying certain assumptions (e.g. about evapotranspiration)?

Author's response: The underlying assumption of this work is that the relationship between precipitation, runoff and evaporation for each location will remain unchanged. As the required precipitation is derived from the GRACE observations, it inherits the relationship between P and ET based on equation 1. Therefore, the estimated required precipitation includes the impact of evaporation and runoff loss.

Specific comments

I would recommend to work through the manuscript again to remove grammatical/syntactic errors. Some examples: - [Page1 Line30] Missing commas, 'the', and 'and/or' (should also be checked: and/or is needed before last item of a list), suggestion: '. . . developing parts of the world, for example, the 2011 East Africa drought or the 2018 dry corridors of central America (REF).'

Author's response: Modified and references added

"example the 2011 East African drought (Lyon and DeWitt, 2012) or the 2014-16 dry corridors of central America (Guevara-Murua et al., 2018) ."

- [Page2 Line56] have/has and "the" too much, suggestion: '. . . is independent of other drought indices and has global spatial coverage.'

Author's response: Modified the sentence. "The GRACE-based drought index is independent of the meteorological estimates and their combined uncertainties."

- [Page2 Line69] singular/plural, citing brackets, suggestion: '. . . reviewed different kinds of drought and their prediction methods based on statistical, dynamical, and hybrid methods. Panet et al. (2013) were ...' –

Author's response: Corrected the citing bracket and singular/plural

[Page3 Line91] add date of last access for websites –

Author's response: Added the access date

[Page4 Line146] be consistent with required precipitation/required-precipitation – [Page 5 Line 181] be consistent with figure/Figure and section/Section - [Page5 Line190] estimated precipitation → reconstructed precipitation - [Page5 Line202] be consistent with climatology/annual signal

Author's response: Changed to a consistent expression

References that should be added: - [Page2 Line59] Reference for global gridded assessments –

Author's response: Reference added (Gerdener et al., 2020; Li et al., 2019)

[Page2 Line62] Reference for increasing frequency of drought –

Author's response: Reference added (Cook et al., 2014)

[Page3 Line98] Reference for cubic convolution interpolation

Author's response: Reference added (Keys, 1981)

[Page2 Line77] Please explain why only terrestrial water storage can be used instead of, for example, in-situ groundwater data.

Author's response: A line added.

"With the sparse availability of in-situ groundwater observations and limited soil moisture observations upto top 5cm of the soil, complete profile of the water stored in a column can only be obtained from the GRACE-based terrestrial water storage." (line 105)

[Page2 Line81] It could be added that you focus on sub-decadal drought because there are only about 15 years of GRACE data.

Author's response: Modified the line as below:

"Here, we focus on sub-decadal drought only because of the availability of GRACE data for 15 years. The study can be extended for a longer time frame with the GRACE- follow on observations. "(line 117)

[Page2 Line83] GPCP was not introduced yet.

Author's response: corrected as Global Precipitation Climatology Project (GPCP)

[Page3 Line114] "Here, we define 'recovery' as a return to the climatological storage state for a given month." This is not totally clear to me, does it mean that the deviation from current dTWSA to the climatology itself in a specific month, which is referred to as severity in Thomas et al. (2014), is already the recovery?

Author's response: Yes, decrease in severity is recovery in a particular month.

[Page3 Line123] state of drought → severity of drought?

Author's response: severity of drought changed to intensity of drought

[Page4 Line125] Could you mark the three recovery periods in Figure 1, please? It seems as if the recovery periods are longer than 1.5, 1 and 0.5 years.

Author's response: Thanks for pointed out. Yes, each grid is two years so it is almost 4, 2 and 1 years.

[Page5 Line167] ... are statistically analyzed using the methods of . . .

Author's response: Added "using signal decomposition "

[Page5 Line187] How was the number 10-14 months for autoregression chosen?

Author's response: Based on the duration of significant auto-correlation with inter-annual signal.

[Page5 Line184] The annual signal and linear trend extracted by signal decomposition [Page5 Line200] worst → worse. [Page5 Line201], [Page7 Line271], and [Page7 Line283] etc.: 'In these regions...', 'this region', and 'monsoon regions' be precise which regions. [Page5 Line202] robust → dominant

Author's response: corrected

[Page6 Line211] Where (reference) is it defined that one sigma represents a wet year

and three sigma an exceptionally wet year?

Author's response: These conditions are assumed in to generate three scenarios, the sentence is modified accordingly.

"one standard deviation wetter than normal precipitation is assumed as wet month and three standard deviations wetter than normal precipitation is assumed as exceptionally wet month."

[Page6 Line220] providing a minimum and maximum baseline?

Author's response: Even in an exceptionally wet scenarios in the dry season, the system fails to recover. Therefore, it does not provide a maximum baseline.

[Page6 Line232] “In Figure7, observed precipitation (red dashed line) and absolute required precipitation (blue line) ...” This was already said.

Author's response: Deleted

Figure 7: This was quite hard to analyze. I would recommend to enlarge the subfigures or put them in a different order (e.g. 4 x 1).

Author's response: Modified

[Page6 Line241] some drought → drought

Author's response: Deleted ‘some’

[Page6 Line241] Remove ‘it is a random selection of the month for’

Author's response: Removed

[Page7 Line254] blue → red?

Author's response: Corrected the color

[Page7 Line256] Is with 80% the total global land area or the masked global land area meant?

Author's response: Masked global area.

4.2.2 Different precipitation scenario → Precipitation scenarios
[Page7 Line 265] ‘We stimulated one-month (February 2016) recovery period ...’ Not

Author's response: clear what is meant

This section shows the recovery percentage within a month based on the three precipitation scenarios.

[Page8 Line288] Better more precise: Here we define drought severity and duration using ...

Author's response: Added ‘drought intensity and duration’

5 Discussion: Refer to section if different aspects/findings are discussed. [Page8 Line298] soil water column → water column

Author's response: Deleted ‘soil’

[Page8 Line 299] Position of sentence in paragraph awkward in the previous context.

Author's response: Deleted the sentence

[Page9 Line327] Also shown in Figure 11 . . .

Author's response: Added (as shown in figure 8)

[Page9 Line342] 1) the independence from other drought indices → more precise, which independencies?

Author's response: Added names of indices (PDSI, SPEI, SPI). Thanks

All Figures: Please check figure references in the text, some of the references have been mixed up. Make sure that all figure captions and title really describe what is shown (compared to what) e.g. Figure 4 fraction of a), b), and c) to what? Total of all. . . or Figure 9 validation of what by what? And consider changing colorbars, since some figure might better be represented in a different way, e.g. Figure 9 discrete colorbar.

Author's response: Modified most of the figures, please see the attachment. Many thanks for the very detailed review and constructive comments.

Reviewer 3:

We appreciate the constructive comment. We went over the paper and tried to improve it by adding more clarification and improving the figures. Modifications in the manuscript are shown in quotation marks

The authors devise a novel method for estimating intradecadal drought recovery peri- ods using GRACE and precipitation data globally. The total water storage estimates from GRACE are used to determine the deficit and the precipitation data is used for estimating the drought recovery periods using an empirical forecasting model. The is- sue is an important one in the context of ongoing climate change. Furthermore, the subject matter is also relevant for the journal and its audience. Having said that there are methodological issues in the data analysis which I will point out in the subsequent section, and the manuscript requires improvement in its narrative.

1.The title does not fully reflect the content of the manuscript. Firstly, the work only looks at short-term (intradecadal) droughts and secondly it uses precipitation in addition to GRACE to estimate the drought recovery times. These two aspects of the manuscript should be reflected in the title. Currently, going by the title, the drought recovery time is solely estimated from GRACE, which is incorrect.

Author's response: Thanks for bringing this up, we have modified the title as follows:

“Estimation of hydrological drought recovery based on precipitation and GRACE water storage deficit”

2.The central goal of the manuscript seems to be to determine drought recovery times and that is facilitated by precipitation forecasts, and the majority of the manuscript is dedicated to figuring out an empirical way to predict precipitation. However, in the conclusions there is hardly any mention of precipitation and the empirical forecast model, and their role in drought recovery times. Rather it is concluded that the one of the findings is that GRACE can be used to derive drought indices, which appears to have been established by Thomas et al (2014).

Author's response: We understand the reviewer’s concern. We mentioned in the manuscript that the precipitation forecast is not the focus of this work, so we preferred not to discuss it. The main idea of precipitation prediction is to generate 3 scenarios and it is mentioned. Section 3.3 states that ‘Note that the motivation for providing a precipitation forecast here is not to present a state-of-the-art precipitation prediction, but to demonstrate the potential utility of the terrestrial water storage deficit in determining required-precipitation and estimating a likely time to recovery. This methodology could be augmented with any type of more complex precipitation forecasting approaches.’

I agree, Thomas et al (2014) has already established that GRACE can be used to derive drought indices. However, the conclusion emphasis its importance in the estimation of required precipitation, as following: ‘GRACE based drought index is valid to estimate the required-precipitation for drought recovery.’

3. Throughout the manuscript it is not clear as to what type of drought the authors are trying to quantify. In the title it is indicated that the authors are concerned about hydrological droughts, but nothing much is said in the manuscript. In the introduction they specify there are multiple definitions of droughts, but beyond that there is no indication on what sort of droughts the authors are interested in and which sorts will be sensitive to the method developed in the manuscript. It would be beneficial if the authors clarify this for the readers.

Author's response: Thanks for bringing this up, we modified a sentence in the introduction. 'This study focusses on hydrological drought, which requires, combining both surface (snow and surface water), and subsurface (soil moisture and groundwater) hydrological information. '

4. For the data the authors use GRACE JPL mascons for total water storage and GPCP for precipitation. Given the wide variety of data available both for total water storage (CSR mascons, GSFC mascons, CSR, GFZ, JPL, ITSG spher- ical harmonics, COST-G combined solutions) as well as precipitation (GPCC, CRU, Delaware), it would be interesting to know how different the drought recov- ery times would be if we were to choose a different pair of datasets. At least in the case of GRACE it should be tested, because it is the starting point for the method proposed in the manuscript. Given the lack of consensus on which GRACE flavour is to be used, or how to reconcile the data, it is worthwhile to perform this test.

Author's response: We understand the reviewer's concern about the possible discrepancies between different GRACE solutions, as they are produced using different approaches by different centers. We added a couple of lines in the GRACE section and added a supplementary material comparing different GRACE solution for an example location. In this study we used JPL based mascon GRACE solution as it has a relatively similar spatial resolution (3°x 3°) as that of GPCP (2.5°x 2.5°). We have also acknowledged that though GRACE mascon and GPCP 2.5 degree is considered as comparable, nevertheless areas of the unit representations are different at different locations. Following lines are added in the section 2.1

"The GRACE level-3 solution is available from different centers are produced using different approaches (spherical harmonics or mascon), different filers, smoothing factors, etc. and eventually, there can be discrepancies between different TWS estimates from GRACE solutions (Jing et al., 2019). The differences between GRACE solutions from different centers are mostly very small at a basin level and lie within the error bounds of the GRACE solution itself (Sakumura et al., 2014). However, at 0.5-degree grid the difference between the amount of missing water estimated by the different GRACE solutions increases substantially (as seen in the supplementary material). This caveat can be mitigated in future by using ensemble of GARCE products. Nevertheless, they are consistent with the detection of drought duration. Please look into the supplementary material for the comparison between water storage deficit estimated by the different GRACE solutions.

In the conclusion section following lines are added

‘However, careful cautions are warranted to interpret the GRACE signal at 0.5 degree grid due to different post processing techniques applied by different GRACE solutions to overcome the inherent limitation in the spatial resolution of GRACE.
Significant ant difference in intensity of drought is observed by different GRACE solutions. Nevertheless, all GRACE solutions have same drought duration.’

Supplementary material

The official GRACE Science Data System continuously released monthly GRACE solution for three different processing centers: GeoforschungsZentrum Potsdam (GFZ), Center for Space Research at University of Texas, Austin (CSR), and Jet Propulsion Laboratory (JPL). These three solutions used different parameters and strategies, such as different degree and order, spherical harmonic coefficient, spatial filter and smoothing factor (Jing et al., 2019). The JPL mascon (JPL-M) and CSR mascon (CSR-M) solutions were provided at 0.5 degrees at https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/ and http://www2.csr.utexas.edu/grace/RL05_mascons.html respectively. GFZ produces only spherical harmonic solution (GFZ-SH), which is downloaded from http://isdc.gfz-potsdam.de/grace-isdc/.

Figure11 shows water storage deficit and estimated required extra precipitation to overcome the drought based on three different GRACE solutions, using the method described in the article for an example location in India (centered on 77.25°E 15.25°N). Sakumura et al., 2014 demonstrated that at a basin-scale, the differences between them are very less. However, the plot shows that there are discrepancies between the amount of missing water at 0.5degree grid because every center has a different method to downscale GRACE inherent spatial resolution to high-resolution grid. Figure 11a shows the detrended climatological anomaly of the three GRACE solutions and cumulative GPCP precipitation has similar variability. The negative anomaly from climatology is considered as drought and is plotted in figure11b. It shows that the difference between CSR and JPL solutions are relatively less than GFZ solution because the first two are the mascon-based solution and are available at 0.5-degree grid (after scaling), while GFZ solution is spherical harmonics based and is re-gridded to 0.5 degree from 1-degree spatial resolution by simple bilinear interpolation. Based on the linear relationship between cumulative detrended GPCP anomaly and detrended GRACE anomalies, required extra precipitation is estimated (figure 11c). The figure shows that the required precipitation varies based on GRACE solutions. Nevertheless, all three GRACE solutions are consistent with the detection of drought duration.

a.

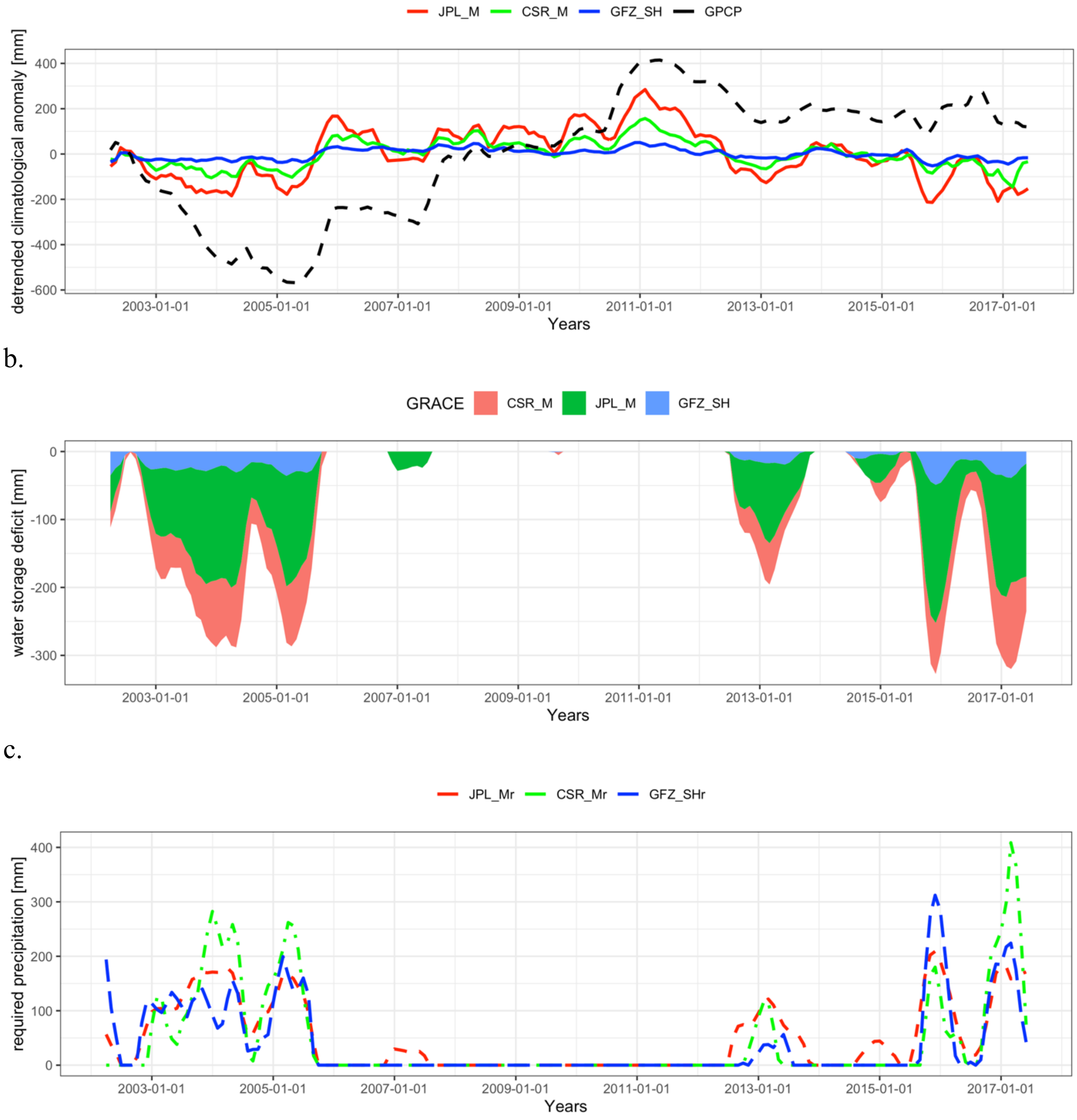


Figure 31: Water storage deficit and estimated required precipitation based on the spherical harmonic solution from GFZ and the mascon solutions from CSR and JPL .a. Cumulative detrended precipitation anomaly (cdPA) compared with the detrended storage anomaly (dTWSA). b) The negative residuals from the GRACE climatology considered as drought. c) Surplus required-precipitation is estimated based on the linear relationship between dTWSA and cdPA, to fill the storage deficit (middle panel)).

Jing, W., Zhang, P. and Zhao, X.: A comparison of different GRACE solutions in terrestrial water storage trend estimation over Tibetan Plateau, Sci Rep, 9, doi:10.1038/s41598-018-38337-1, 2019.
Sakumura, C., Bettadpur, S. and Bruinsma, S.: Ensemble prediction and intercomparison analysis of GRACE time-variable gravity field models, Geophysical Research Letters, 41(5), 1389–1397, doi:10.1002/2013GL058632, 2014.

Yes, we agree, there are many precipitation products like CRU, GPCC, etc. However, GPCP is a widely used global precipitation data. GPCP combines the strength offered by in situ as well as satellite data. In many regions of the world in situ data are sparse, so using a product that only utilizes in situ data may not be the best choice. GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al. 2018). Besides, in section 3.3 historical analysis of the data is done using 1979-2017 precipitation data. For this period GPCP is the best available data.

Following sentences are added in the GPCP section
“Global Precipitation Climatology Project (GPCP) is a widely used global precipitation data. Most of the other observational products don’t produce precipitation estimates beyond 60deg S/N for longer historical period (1979 – present). Besides, GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al., 2018)
Behrangi, A., A. Gardner, J. T. Reager, J. B. Fisher, D. Yang, G. J. Huffman, and R. F. Adler (2018), Using GRACE to Estimate Snowfall Accumulation and Assess Gauge Under catch Corrections in High Latitudes, Journal of Climate, 31(21), 8689-8704, doi: 10.1175/jcli-d-18-0163.1.”

5. The GRACE and the GPCP datasets are represented on 3° spherical cap and 2.5° × 2.5° equi-angular grid. After indicating that the area of the unit representations are comparable, they represent the two datasets on a 0.5° × 0.5° grid to perform the analyses. There a couple of issues here. Firstly, the difference between the areas of the unit representations are at best ≈ [10, 000]km^2 (at the equator) and at worst ≈ [80, 000]km^2 (close to the poles). Secondly, by regridding them to a smaller grid size, they are only making map a bit smooth, but there is no change in the information content. The best way to bring them to a commensu- rate resolution to perform the data analysis would have been to filter them with a common filter either a Gaussian or any other contrast preserving filter, and then regrid them to any other grid size they wanted. It is essential that the authors discuss the impact of these data processing choices on the final results.

Author's response: Thanks for bringing it so precisely. The mascon solution in the study is re-gridded by multiplying it with a scaling factor, to improve the interpretation of signals at sub-mascon resolution. This is essential as the shape and size of mascon changes with latitude. We agree that there are significant differences between the mascon (3x3 grid) and GPCP (2.5) area at different locations. The Following sentence is added in the GPCP section, thanks for the comment with numbers.

“Nevertheless, areas of the unit representations are different in tens of thousands km^2 at different locations which get worst towards pole. We also acknowledge the possible caveat due to different methods of re-gridding of both the datasets, which can be improved in future work. However, as drought is a smooth process the impact of neighboring pixels should not affect the analysis significantly. ”

Based on these comments I recommend a major revision.

3 Technical comments

30 Please provide references for the events you have described

Author's response: Reference added

example the 2011 East African drought (Lyon and DeWitt, 2012) or the 2014-16 dry corridors of central America (Guevara-Murua et al., 2018)

32 Please provide standard references for the drought definitions, for e.g., Wilhite and Glanz (1985). Water International

Author's response: Added (Wilhite and Glantz, 1985)

33 It is not clear what you want to convey by indicating the different indices.

Author's response: In this study GRACE TWS is used as a drought index, therefore it is essential to describe some other common drought indices and their limitations. The paragraph has been restructured to make it clearer.

38 Similar is the case for remote sensing data based drought indicators. Please clarify to the reader what their benefits and shortcomings are in order to get a perspective.

Author's response: Thanks, we added the following line in the introduction

“With the sparse availability of in-situ groundwater observations and limited soil moisture observations (up to top 5cm of the soil), a complete profile of the water stored in a column can only be obtained from the GRACE-based terrestrial water storage.”

51 "This method can improve ..." until end of line 55. Please corroborate the state- ment, if it is not a conclusion of Thomas et al (2014).

Author's response: The lines are moved to a paragraph below to separate it from Thomas et al. paper discussion and a line added to it.

… This quantification of total required storage for drought recovery can only be estimated using GRACE observation.

59 "... are still a few" Please cite some of those studies

Author's response: Reference added (Gerdener et al., 2020; Li et al., 2019)

63 successive –> next

Author's response: Changed

74 "However, above average ..." until end of line 77. Please clarify whether it is your opinion or a conclusion of Pan et al (2013)

Author's response: Following line is added to separate it from Pan et al paper.

Pan et-al., approach is exclusively precipitation based, however, …

84 In general, the introduction lacks a cogent narrative. It is hard to identify what issue you are trying to address

Author's response: Added a line “The intellectual contribution of this paper is in the estimation drought recovery and conceptually bringing a framework for drought recovery forecast based on precipitation deficit. “

88 "... global and regional water cycle." Please provide a reference for the same.

Author's response: Added global (Eicker et al., 2016; Fasullo et al., 2016) and regional water cycle (Singh et al., 2018; Springer et al., 2017)

104 When you say comparable, please indicate the numbers.

Author's response: we discussed that 3 degree Mascon and 2.5 degree GPCP data products are comparable in spatial terms. Additionally, as per your suggestion area details are added in the GPCP section.

135 Please clarify to the reader why you need to integrate the precipitation time- series.

Modified the line as follows:

The smoothed and detrended precipitation anomaly is then integrated in time to get storage anomaly, which is termed as cumulative detrended smoothed precipitation anomaly (cdPA).

142 The variability of precipitation intensity can be checked. It is unclear why this needs to be assumed.

Author's response: This assumption is for the estimation of required precipitation to consider the relationship between precipitation and storage variability stable. For example, a region having mostly slow rain has one kind of storage-precipitation relationship and if it gets unusual heavy rain then the relationship changes. Therefore, we assume here, that there is less variability in the precipitation intensity of a region.

189 The paragraph reads like the caption of Figure 5. Please interpret the figure for the reader as to what you want to convey through that figure.

Author's response: Thanks, a couple of sentences added.

“This precipitation reconstruction skill is used for a simplistic normal forecast. Further, two additional precipitation scenarios are simulated by adding respectively one and two standard deviations of precipitation to the normal forecast, which is used in probability recovery analysis.”

199 Is the NSE performed on the full signals or after removing the climatology sig- nal? It is well known that the climatology will dominate the metric if it is retained. Please clarify.

Author's response: Many thanks for the correction, NSE section is removed.

204 In Figure 6, please indicate the regions of weak association. Also, instead of a continuous scale, it would be better to use a discrete scale colorbar, i.e., one colour for a range of values. It is more convenient for the human eye to interpret such images.

Author's response: Regions dominated by sub-seasonal signal has a weak association. Modified the figure

265 stimulated –> simulated?

Author's response: Corrected

299 "hydrological compartments" – Do you mean storage compartments?

Author's response: Modified: hydrological storage compartments

342 "independency from other drought indices" – Do you mean to say that SPI de- pends on other drought indices? Please clarify the "independence" argument.

Author's response: Modified: The GRACE-based drought index is independent of the meteorological estimates and their combined uncertainties

343 "spatial coverage" – Indices based on NDVI also cover much of the globe. How is this an advantage specific to the GRACE method?

Author's response: Modified: The GRACE-based drought index is independent of the meteorological estimates and their combined uncertainties

Apart from the specific comments, I would like to indicate that it was rather frustrating to read such a methodology-heavy manuscript devoid of any equations. Even if the equations involved are simple and straight-forward I believe they will provide clarity for the reader. Please consider incorporating equations.

Author's response: Equation and it description added

$$dS/dt = P - ET - R \qquad \text{Eq. 1}$$

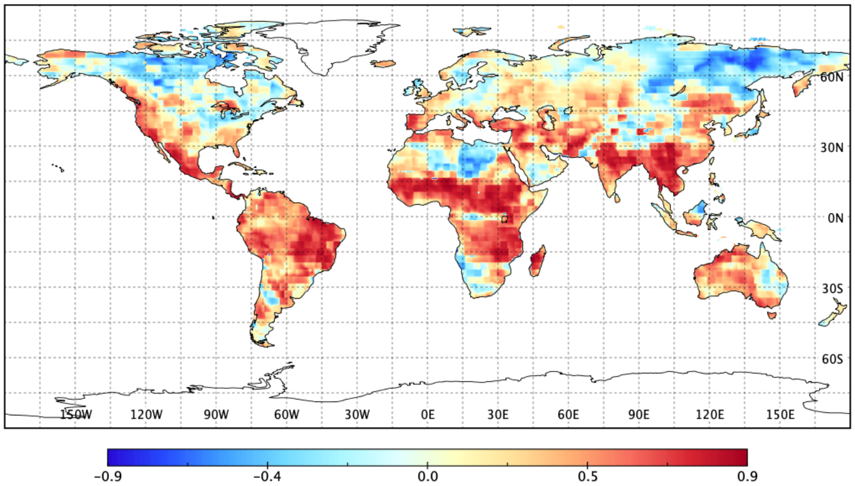
The water balance equation based on hydrological fluxes (Eq. 1) shows that the change in terrestrial water storage (dS) in a region for a given month (dt) depends on is the monthly precipitation (P, mm/month); evapotranspiration (ET, mm/month) and streamflow (R, which includes both surface water and subsurface water) (Swenson and Wahr, 2006). Assuming the relationship between precipitation and ET + R remains constant for a region, the variability in precipitation gives an idea of possible variation in the storage.

Swenson, S. and Wahr, J.: Estimating Large-Scale Precipitation Minus Evapotranspiration from GRACE Satellite Gravity Measurements, J. Hydrometeor., 7(2), 252–270, doi:10.1175/JHM478.1, 2006.

Your results largely fall into the sequential and diverging types of data for which colorbrewer2.org provides very good advice on choosing colorbars. Typically, sequential data require only one colour with varying intensity to indicate the sequences and diverging data requires two colours of varying intensities. Furthermore, the standard colorbars are not color-blind friendly. I strongly recommend that you follow the rules indicated in the website to improve the graphics in the manuscript.

Author’s response: All of the maps are modified with new color bars, please check the attachment.

a. Correlation coefficients



b. Regression Coefficients

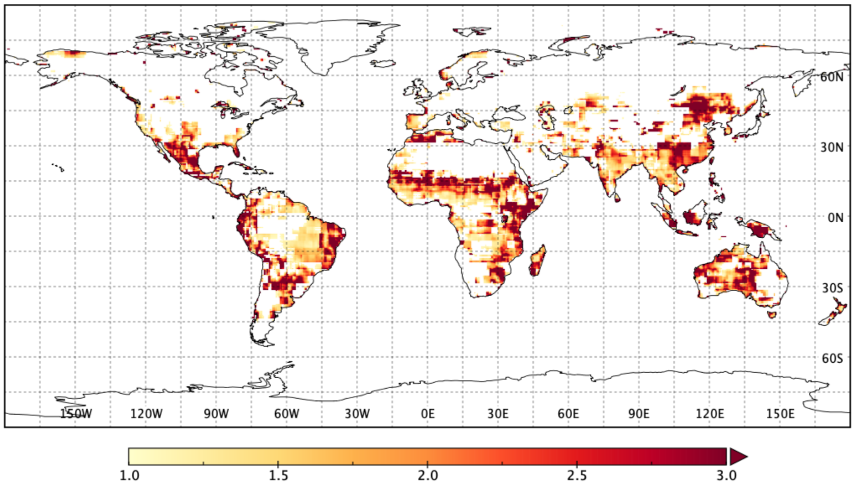
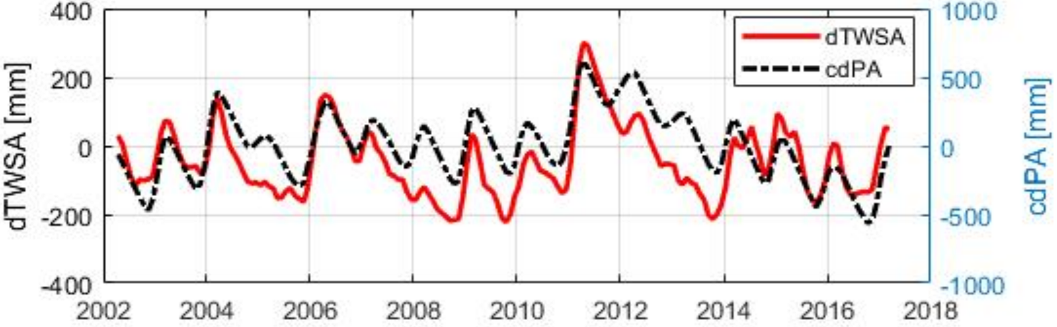


Figure 2: a) Correlation coefficients and, b) regression coefficients between cumulative detrended precipitation anomalies (cdPA) and detrended terrestrial water storage anomaly (dTWSA).

a. Precipitation-storage association



b. Estimation of required-precipitation

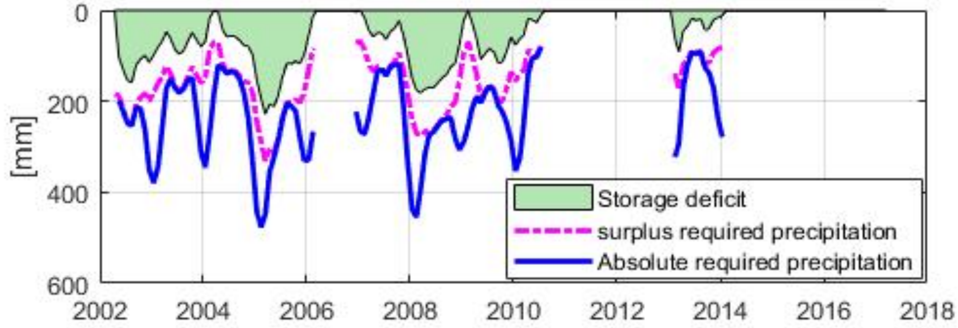
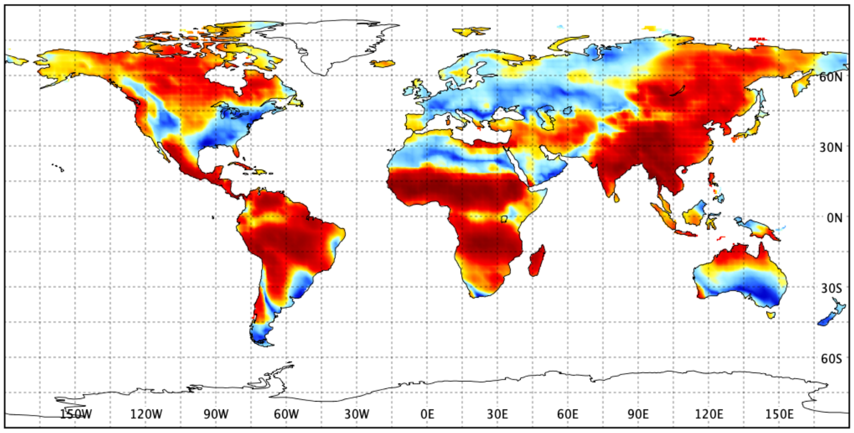
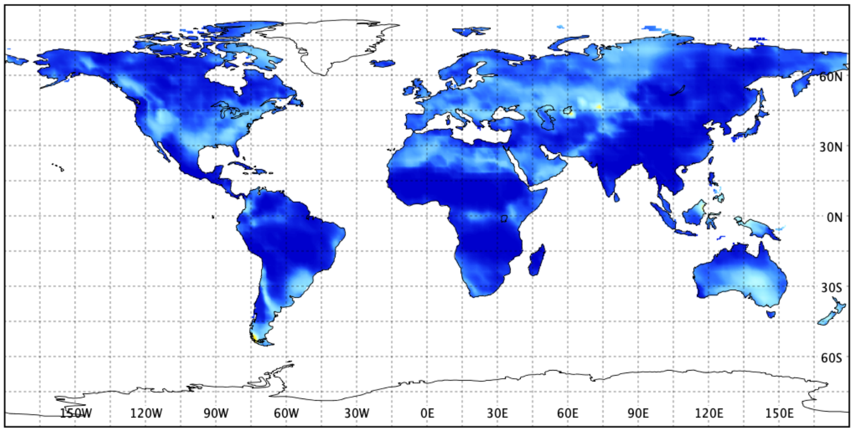


Figure 3: Estimation of the required-precipitation at an example location. a) Cumulative detrended precipitation anomaly (cdPA) compared with the detrended storage anomaly (dTWSA). b) Surplus required-precipitation is estimated (magenta plot) from the linear relationship between dTWSA and cdPA, to fill the storage deficit (green plot). Then precipitation climatology is added to obtain absolute required-precipitation (blue plot).

a. Annual Signal



b. Linear trend + inter-annual signal



c. Sub-seasonal signal

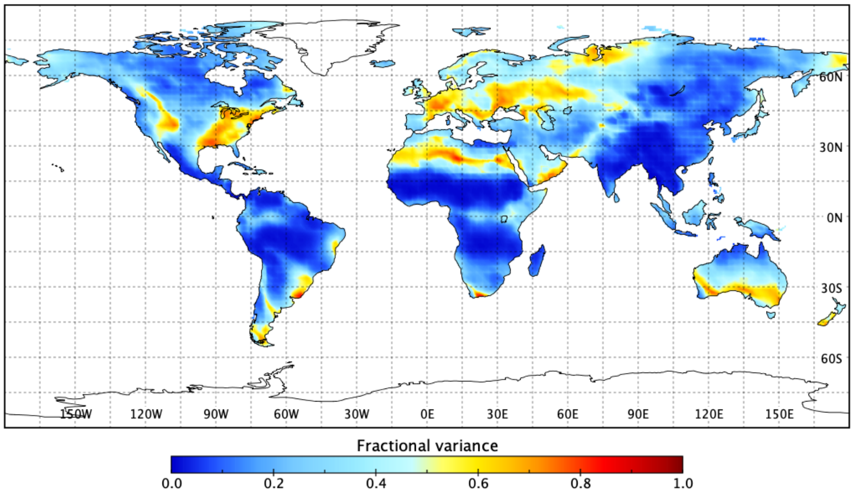


Figure 4: Fractional variance of the decomposed signal to the full signal. a. Annual Signal, b. Long-term signal, c. sub-seasonal high frequency signal

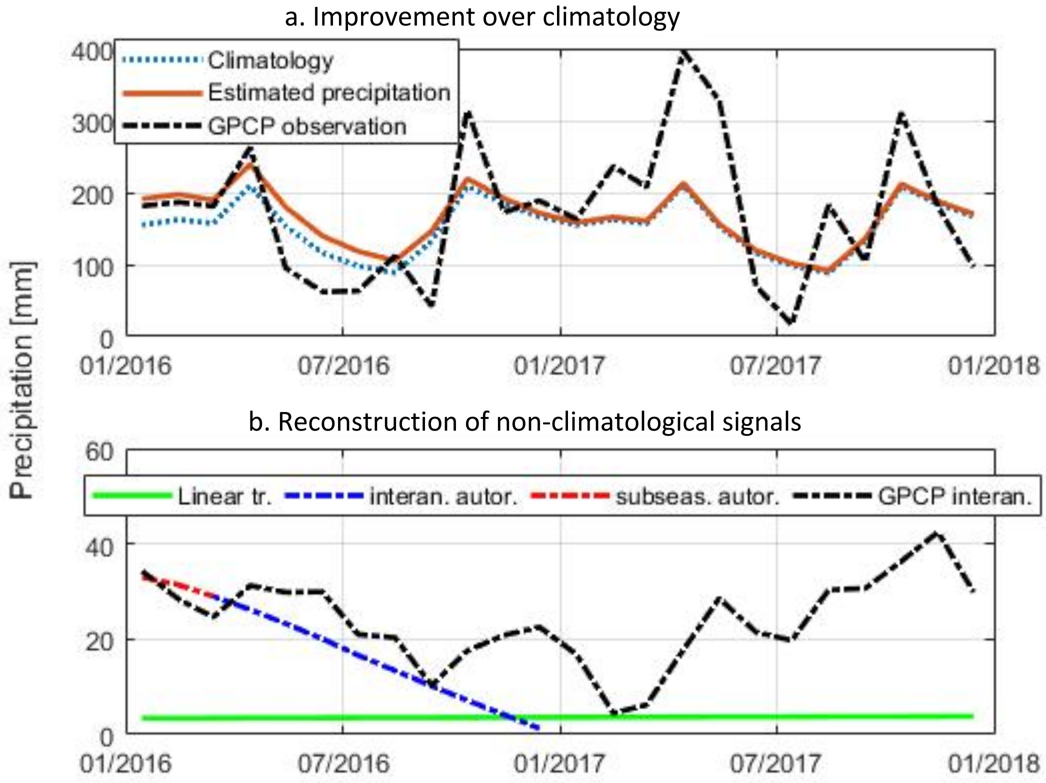
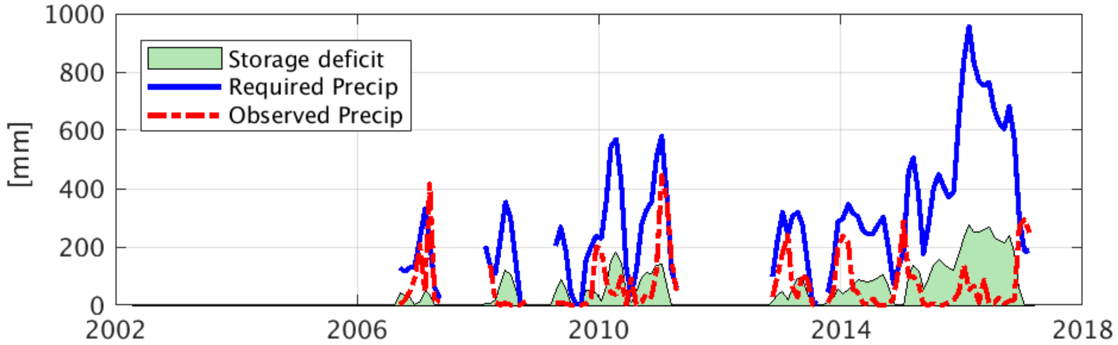
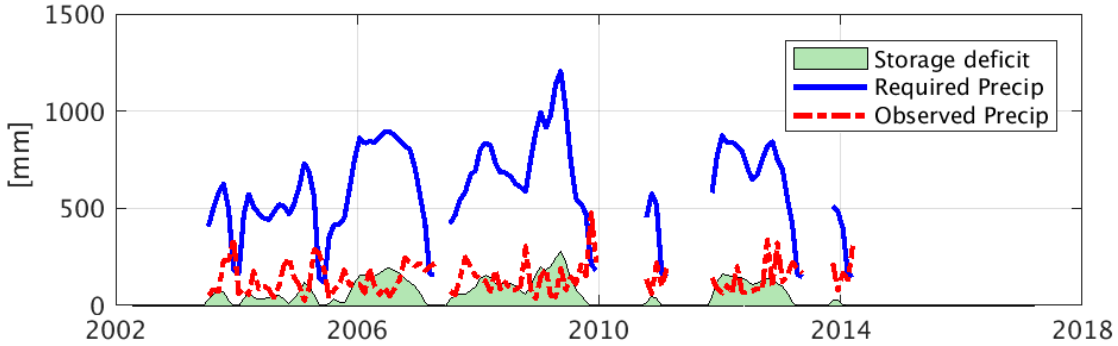


Figure 5: Reconstruction of precipitation signal for 2016-2017. a) The reconstructed signal compared with GPCP observations and its climatology. b) The reconstruction of a long-term secular signal from the linear trend, and inter-annual and sub-seasonal autoregression, compared to GPCP interannual signal.

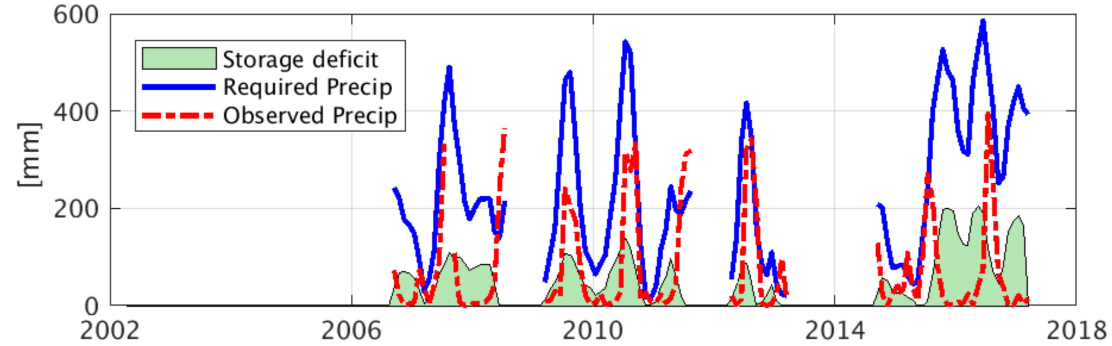
a. NW Australia



b. NE Argentina



c. N India



d. N. Brazil

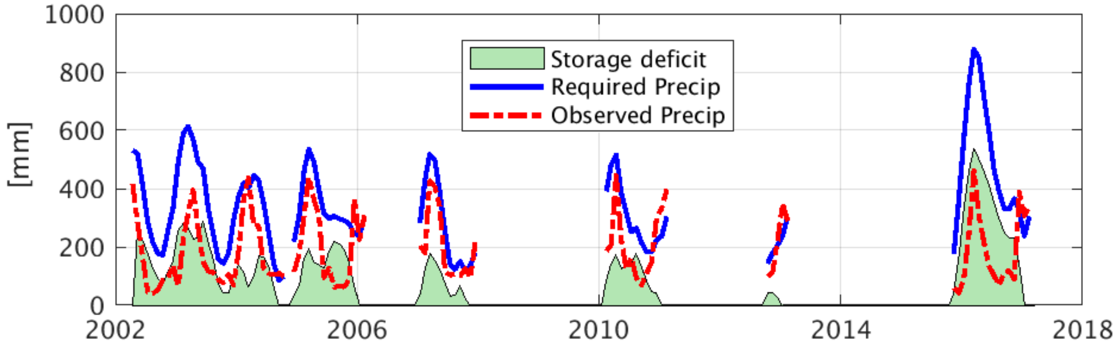
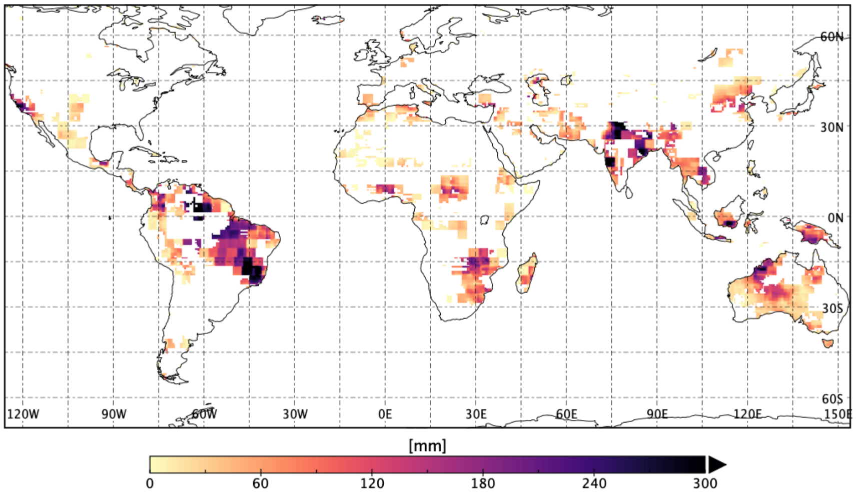


Figure 6 Validation of the required-precipitation estimate by drought recovery estimates at example locations. The different instances of drought show that drought ends (from the perspective of TWSA) whenever observed precipitation (red plot) exceeds the required-precipitation (blue plot).

a. Storage deficit



b. Required precipitation

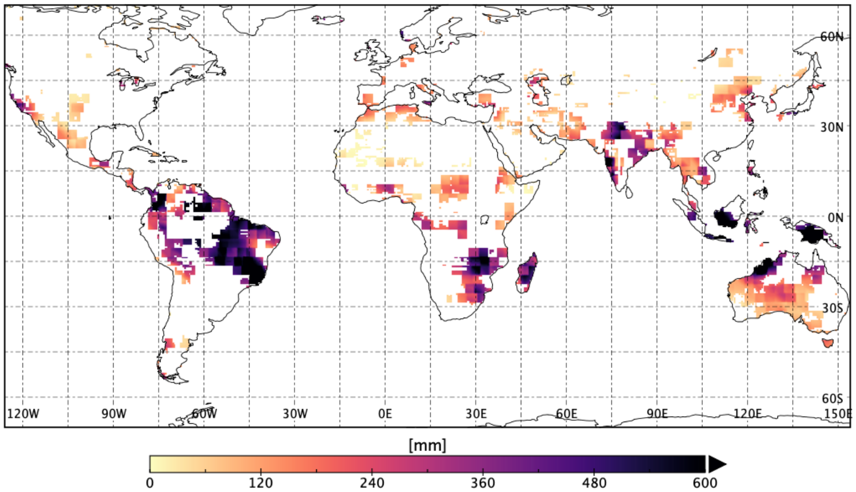
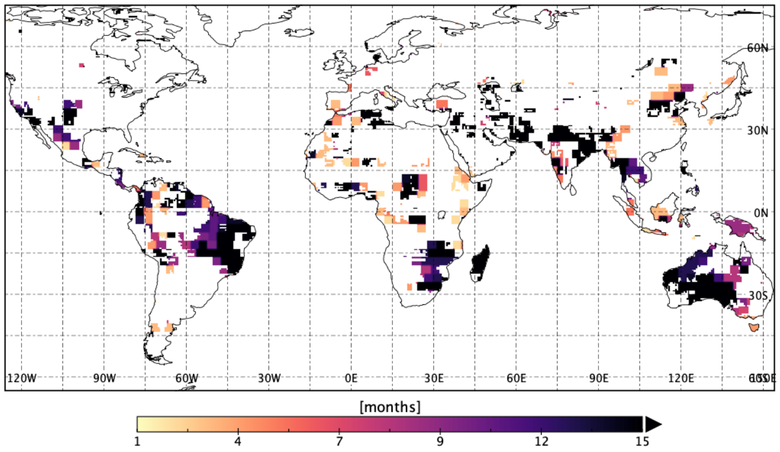
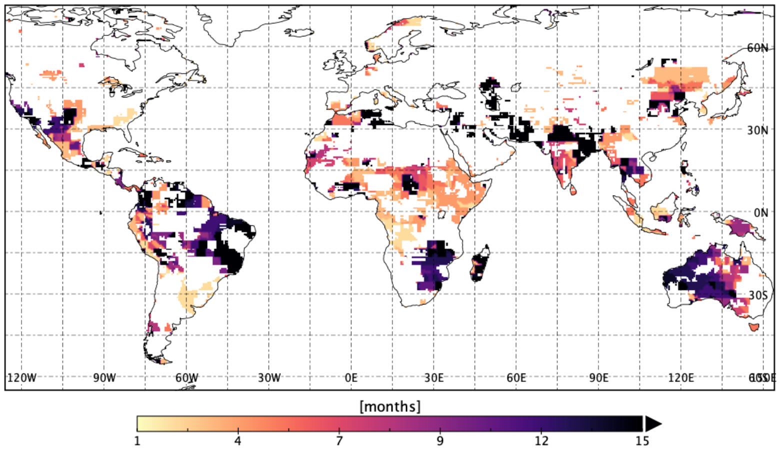


Figure 7: a) Storage deficit in an example month (January 2016). b) the amount of required-precipitation to fill the deficit.

a. Recovery period observed by GRACE



b. Recovery period estimated by the discussed method



c. Consistency in the recovery estimates

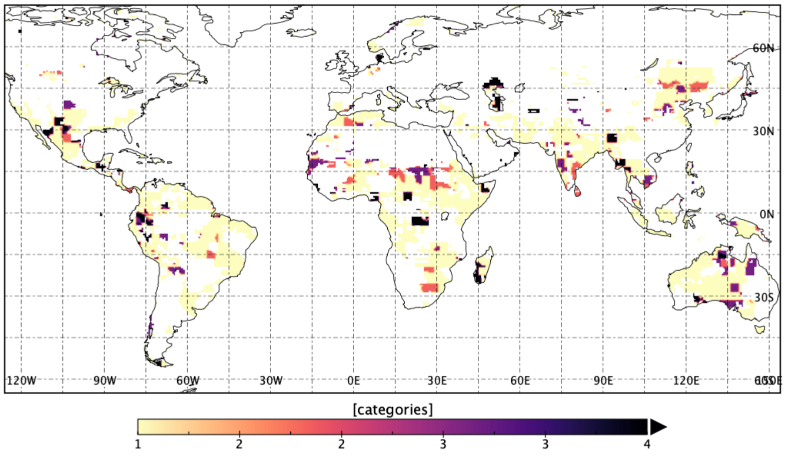
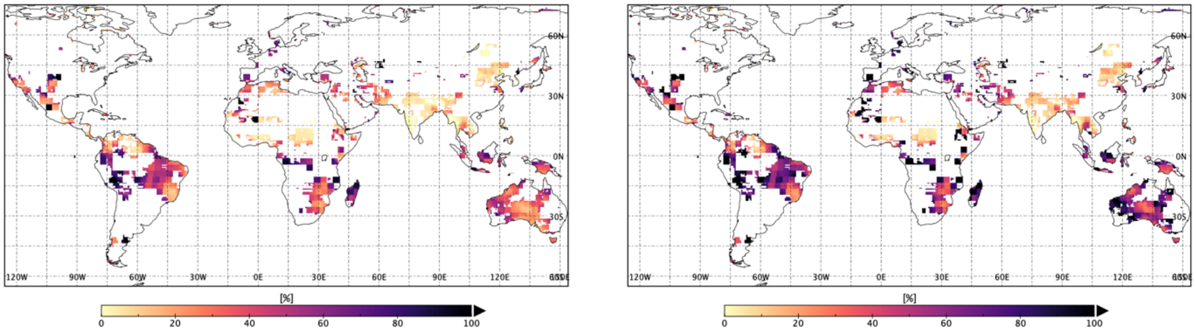


Figure 8: Validation of the estimated required-precipitation by the recovery duration from January 2016 drought observed from: a) GRACE and b) estimated by the discussed method using GRACE and GPCP observations (middle panel). c) consistency in the observed recovery

duration by GRACE and GPCP (1 = 1-2 months difference, 2 = 3-4 months difference, 3 = 5-8 months difference and 4 = 9+ months difference).



a. Normal precipitation

b. 1 std. wetter than normal

c. 3 std. wetter than normal

d. Observed (GPCP) precipitation

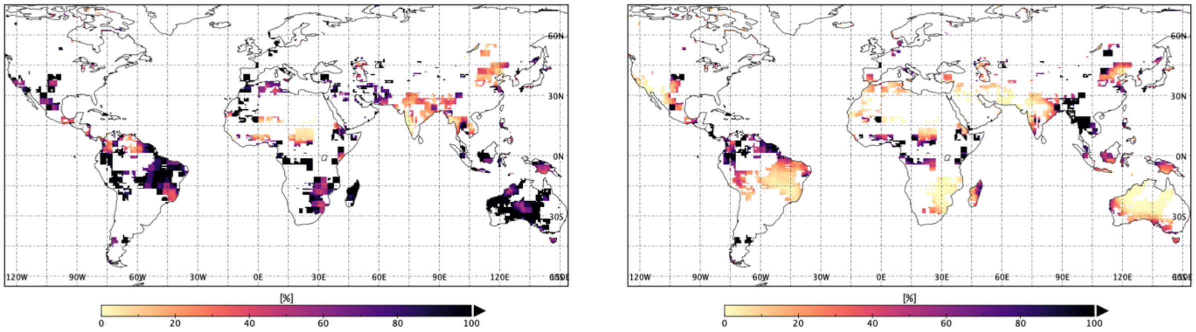
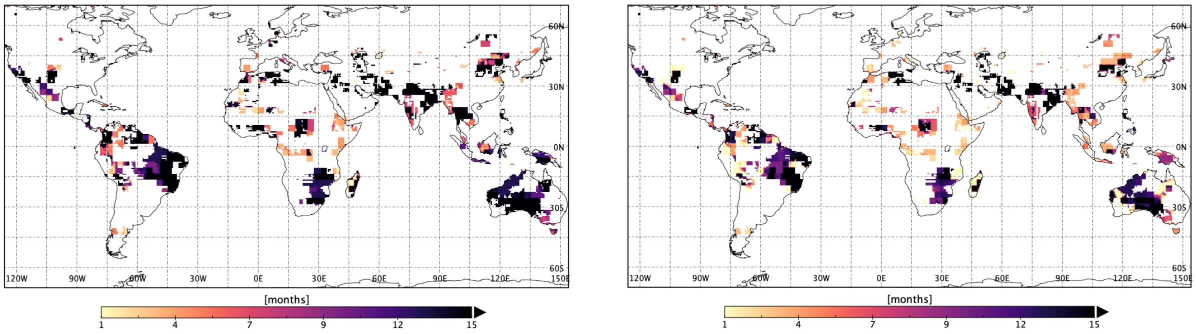


Figure 9: Expected percent recovery in a month given the three different precipitation scenarios and the observed GPCP precipitation.



a. Normal precipitation

b. 1 std. wetter than normal

c. 3 std. wetter than normal

d. Observed recovery duration by GRACE

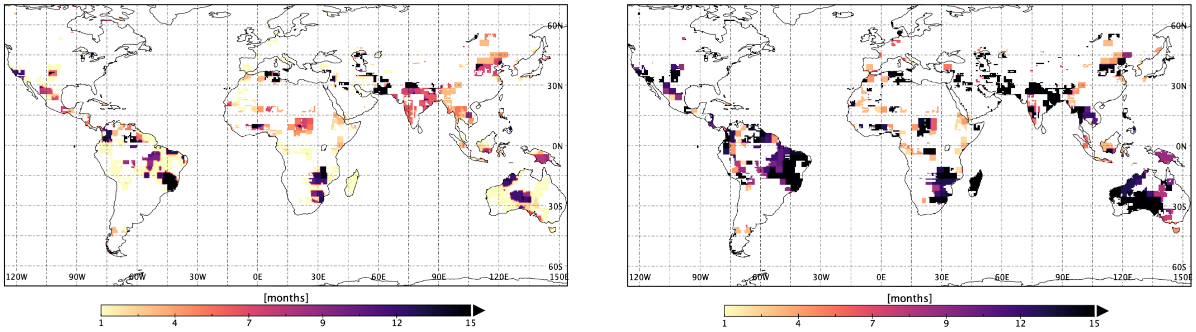


Figure 10. Duration of drought recovery from January 2016, given the three different precipitation scenarios and as observed by GRACE

Estimation of hydrological drought recovery based on precipitation and GRACE water storage deficit

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Abstract. Drought is a natural climate extreme phenomenon that presents great challenges in forecasting and monitoring for water management purposes. Previous studies have examined the use of Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage anomalies to measure the amount of water ‘missing’ from a drought-affected region, and other studies have attempted statistical approaches to drought recovery forecasting based on joint probabilities of precipitation and soil moisture. The goal of this study is to combine GRACE data and historical precipitation observations to quantify the amount of precipitation required to achieve normal storage conditions in order to estimate a likely drought recovery time. First, linear relationships between terrestrial water storage anomaly (TWSA) and cumulative precipitation anomaly are established across a range of conditions. Then, historical precipitation data are statistically modeled to develop simplistic precipitation forecast skill for two years based on climatology and long-term trend. Two additional precipitation scenarios i.e. wet and exceptionally wet are simulated to predict the recovery period by using respectively one and three standard deviations of the normal precipitation forecast. Precipitation scenarios are convolved with water deficit estimates (from GRACE) to calculate the best-estimate of a drought recovery period. The results show that in the regions of strong seasonal amplitude (like monsoon belt) drought continues even with the above-normal precipitation until its wet season. The historical GRACE-observed drought recovery period is used to validate the approach. The estimated drought for an example month demonstrated 80% similar recovery period as observed by the GRACE for the region where storage - precipitation relationship is strong.

1 Introduction

Drought is a widespread recurring natural hazard with several direct and indirect impacts. The shortage of water in an ecosystem not only reduces water availability for human consumption but also causes extensive flora and fauna mortality. Dryland, with little vegetation on the surface, increases soil erosion, reduces water resilience time, and enhances the possibility of forest fires, leading to many indirect disasters. Big historical droughts have affected millions of lives and cost billions of dollars in the last half a century. For example, the 1988 USA drought is estimated to cost $40 billion, 1999 drought in Asia affected 60 million people (Mishra and Singh, 2010). Severe water-crises can put society in turmoil and drive large-scale migrations particularly in the developing parts of the world for example the 2011 East African drought (Lyon and DeWitt, 2012) or the 2014-16 dry corridors of central America (Guevara-Murua et al., 2018).

There are different definitions of drought depending on the context, including agricultural (soil moisture deficit), meteorological (eg. precipitation deficit or increase in evapotranspiration), and hydrological (storage deficit for eg. in streamflow/groundwater) droughts (Behrangi et al., 2015; Mishra et al., 2006; Wilhite and Glantz, 1985). This study focusses on hydrological drought, which requires, combining both surface (snow and surface water), and subsurface (soil moisture and groundwater) hydrological information. To monitor and evaluate drought, several drought indices are available like the Palmer drought severity index (PDSI) (Palmer, 1965), standardized precipitation index (SPI) (McKee et al., 1993), standardized precipitation evaporation index (SPEI) (Vicente-Serrano et al., 2009), etc. They heavily rely on the accuracy of meteorological inputs, hence become unreliable where the ground observations are sparse (Zhao et al., 2017). Additonally use of a consistent drought metrics for various climatic regimes is essential for global drought studies. With the availability of different remote sensing observations, various global drought indices are developed like Normalized differential vegetation index (NDVI) (Keshavarz et al., 2014), Evaporation stress index (ESI) (Otkin et al., 2013), Soil moisture index (SMI) (Sridhar et al., 2008), Soil water deficit index (SWDI) (Martínez-Fernández et al., 2015). These drought monitoring indices are mostly based on a few hydrological parameters (like soil moisture, precipitation, ET) and have no information about the drought recovery period.

Gravity Recovery and Climate Experiment (GRACE) mission enables us to measure the integrated water storage variation in a system, which includes surface water, soil moisture, and groundwater. Many studies have used GRACE to describe the process and monitoring of drought (Awange et al., 2016; Forootan et al., 2019; Sun et al., 2017; Thomas et al., 2014; Yirdaw et al., 2008; Zhang et al., 2015). Yirdaw et al. (2008) were foremost in exploring the potential of GRACE in the drought monitoring in the Canadian Prairie region. Houborg et al. (2012) developed a GRACE-based drought indicator by assimilating terrestrial water storage (TWS) into Catchment Land Surface Model (CLSM) over North America. Thomas et al. (2014), for the first time, used GRACE terrestrial water storage anomaly (TWSA) as an independent global drought severity index by considering negative deviations from the monthly climatology of the time series as storage deficits. While an increasing number of case studies have used GRACE to characterize drought in different regions, for example, Amazon (Chen et al., 2009; Frappart et al., 2012), Texas (Long et al., 2013), China (Zhao et al., 2018), a global gridded assessment of the direct application of GRACE on drought are still a few (Gerdener et al., 2020; Li et al., 2019). Unlike other drought indices, the GRACE-based drought index is independent of the meteorological estimates and their combined uncertainties. The GRACE based index not only provides the total amount of missing water from an ecosystem but also clearly identifies the beginning and the end of a drought, on a monthly timescale. The ultimate benefit of this approach is that by quantifying the amount of water required in storage for a region to return to historical average conditions, the method allows for the identification of an explicit hydrological drought recovery target.

Recovery time can be a critical metric of drought impact, in showing how long an ecosystem requires to revert to its pre-drought functional state (Schwalm et al., 2017). With the increasing frequency of drought (Cook et al., 2014), it is essential for an ecosystem to recover completely before the next drought, otherwise repeated exposure to stress can degrade the ecosystem for a long-term. A tentative estimate of expected recovery can help water management authorities to regulate the water supply until a system recovers completely from drought stress. Previous studies have analyzed historical drought events and different predictors like teleconnections, local climate variables (temperature, precipitation) for drought prediction (Behrangi et al., 2015; Maity et al., 2016; Otkin et al., 2015; Yuan et al., 2013) but not much work has been done on drought recovery analysis. Many studies have analyzed causes and patterns of onset and termination of drought (Dettinger, 2013; Maxwell et al., 2013; Mo, 2011; Seager et al., 2019) but did not dwell into the statistical evolution of drought recovery. Hao et al., (2018) reviewed different kinds of drought and its prediction methods based on statistical, dynamical, and hybrid methods. Pan et al., (2013) were the first to develop a probabilistic drought recovery framework based on an ensemble forecast. They used a Copula model to establish a joint distribution between cumulative precipitation and a soil-moisture-based drought index to fine-tune their correlation structure. They demonstrated that drought recovery estimates typically have significant uncertainty and that a probabilistic approach can offer better information on realized drought risk. Pan et al., approach is exclusively precipitation based. However, above-average rain in a given month may replenish surface water/soil moisture and support recovery in vegetation, but the true impact of drought continues until all hydrological storage compartments, including deep soil moisture and groundwater recover to their normal. In this study, we looked into an integrated hydrological drought recovery phenomenon, which can only be estimated by combining total water storage in all the hydrological compartments. With the sparse availability of in-situ groundwater observations and limited soil moisture observations (up to top 5cm of the soil), a complete profile of the water stored in a column can only be obtained from the GRACE-based terrestrial water storage.

The intellectual contribution of this paper is in the estimation drought recovery and conceptually bringing a framework for drought recovery forecast based on precipitation deficit. Here we explored hydrological drought recovery time at a 0.5-degree gridded framework and focused on sub-decadal drought only because of the availability of GRACE data for 15 years. The study can be extended for a longer time frame with the GRACE- follow on observations. Building upon previous works, we apply GRACE-observed storage deficits as a drought indicator and provide different probabilistic scenarios for drought recovery based on historical precipitation analysis. Specifically, we estimate the required-precipitation to fill a storage deficit by deriving a linear relationship between precipitation and storage variability. Different precipitation scenarios are generated for precipitation inputs based on the distribution of historical observations. The required-precipitation estimates are validated by the duration of drought using the Global Precipitation Climatology Project (GPCP) and GRACE observations independently.

2 Data

2.1 GRACE

The GRACE mission operated from April 2002- June 2017 with a primary goal to track water redistribution on Earth and to improve our understanding of the global (Eicker et al., 2016; Fasullo et al., 2016) and regional water cycle (Singh et al., 2018; Springer et al., 2017). The GRACE-based TWSA includes integrated water mass changes in a vertical column which may consist of rivers, lakes, snow, ice, glaciers, soil moisture, permafrost, swamp, groundwater, etc. The GRACE level-3 solution is officially available from three different centers, which are produced using different approaches (spherical harmonics or mascon), different filers, smoothing factors, etc. and eventually, there can be discrepancies between different TWS estimates (Jing et al., 2019). The differences between GRACE solutions from different centers are mostly very small at a basin level and lie within the error bounds of the GRACE solution itself (Sakumura et al., 2014). However, at 0.5-degree grid, the difference between the amount of missing water estimated by the different GRACE solutions increases substantially (as seen in the supplementary material) because of different downscaling methods. This caveat can be mitigated in the future by using an ensemble of GARCE products. Nevertheless, they are consistent with the detection of drought duration. Please look into the supplementary material for the comparison between water storage deficit estimated by the different GRACE solutions

For this study downloaded the GRACE mascon (RL06) solutions from the Jet Propulsion Laboratory (JPL) website https://grace.jpl.nasa.gov, accessed on 03.03.2019 (Wiese et al., 2018). The gravity field signals of the GRACE are pre-processed to monthly-gridded equivalent water height (EWH) variations by JPL (Watkins et al., 2015; Wiese et al., 2016). The mascon GRACE solutions are provided at a 0.5-degree long-lat grid, but they represent the 3x3 degree equal-area caps. The shape and size of the mascon caps vary with latitude. Therefore, the gridded mascon solutions are multiplied by a scaling factor grid (https://grace.jpl.nasa.gov/data/get-data/jpl_global_mascons/), to improve the interpretation of signals at sub-mascon resolution. Since 2011, the GRACE dataset has data gaps of 1-2 months in every 5-6 months due to the aging batteries of the satellites. However, to compare precipitation and storage variability, a continuous monthly TWSA time-series is required. Therefore, the data gaps in the time-series are filled by cubic convolution interpolation (Keys, 1981).

2.2 GPCP

Global Precipitation Climatology Project (GPCP) is a widely used global precipitation data. Most of the other observational products don't produce precipitation estimates beyond 60deg S/N for the longer historical period (1979 – present). Besides, GPCP applies gauge under catch correction to in situ precipitation measurement, which has been found important to improve snowfall measurement (Behrangi et al., 2018). The latest global monthly precipitation data is obtained from the GPCP V2.3 from their website https://www.esrl.noaa.gov/psd/ (Adler et al., 2003) for 1979-2017. It is a combined satellite-based product, adjusted by the rain gauge analysis. The downloaded 2.5-degree resolution data is re-gridded to 0.5 degrees by using bilinear interpolation to harmonize it with the GRACE grid.

The spatial resolution of the original GRACE solution (3-degree mascon) and GPCP (2.5-degree) are comparable. Nevertheless, areas of the unit representations are different in tens of thousands km^2 at different locations which get worst towards the poles. However, the size and shape of mascons vary with latitude, therefore to improve the interpretation both datasets are brought to the 0.5-degree grid. We also acknowledge the possible caveat due to different methods of re-gridding of both the datasets, which can be improved in future work. However, as drought is a smooth process the impact of neighboring pixels should not affect the analysis significantly.

3 Methods

3.1 Storage deficit

It is useful to know the total amount of missing water from an ecosystem in order to characterize a drought so that an explicit target can be assumed that defines a drought recovery. Currently, global gridded total water storage variations can only be obtained from GRACE TWSA. The TWSA is first smoothed by three months moving average filter, followed by the removal of a linear trend to reduce the impact of long-term signals in the storage. A linear trend in storage variability can be caused by other continuous/long term processes than just precipitation, like upstream water abstraction, groundwater pumping, increase/decrease in snowmelt, etc. We acknowledge the caveat of the possibility of sudo-trend due to unusual signal at the beginning or end of the record in some regions. The reduced TWSA is termed as dTWSA. The deviation of storage (dTWSA) from its normal water storage cycle (i.e., its historical climatology) can give an idea of the severity of drought phenomena. Here, we define 'recovery' as a return of dTWSA to the climatological storage state for a given month. The climatology of the time series is estimated over the 15-year GRACE record (April 2002-March 2017) by averaging values from the same months of each year (i.e., all Januaries, all Februaries, so on). The negative residuals of the dTWSA from its climatology are considered as water storage 'deficit' in a grid cell (Thomas et al., 2014). If the duration of negative residuals is longer than three months, we designated it as a drought event. If recurring drought happens within a month gap (i.e., recovery shorter than one-month duration), we considered it a continuation of the same drought. The green plot in Fig.1 shows the duration and severity of recurring drought in an example location in Australia (centered on 133.75°E 16.75°S). Using this approach, we produce a global gridded drought characteristics record, which includes the frequency, intensity, and duration of drought, for 2002-2017 period. For any instance and location, the state of drought and its length can be identified by quantifying the water storage deficit from dTWSA. Eventually, recovery duration for each drought can also be observed, i.e., how long negative residuals from climatology continued. For instance, Figure-1 shows three major droughts and their respective recovery periods (of nearly 4, 3, and 1 year) for a sample location in Australia.

Figure 1

3.2 Estimation of the required-precipitation for storage deficit

$$dS/dt = P - ET - R \qquad \text{Eq. 1}$$

The water balance equation based on hydrological fluxes (Eq. 1) shows that the change in terrestrial water storage (dS) in a region for a given month (dt) depends on is the monthly precipitation (P, mm/month); evapotranspiration (ET, mm/month) and the streamflow (R, which includes both surface water and subsurface water) (Swenson and Wahr, 2006). Assuming the relationship between precipitation and ET + R remains constant for a region, the variability in precipitation gives an idea of possible variation in the storage. The amount of required-precipitation to overcome a deficit can be estimated using the association between precipitation and terrestrial water storage anomaly (TWSA). Monthly GPCP observations are first reduced by their mean for the April 2002 – March 2017 period (i.e., the 15-year GRACE data record) to obtain precipitation anomaly. Then the relationship between precipitation and storage anomalies is derived. For this, first, both variables are smoothed by a three-month moving average low pass filter to remove high-frequency noise. Then, their linear trends are removed to reduce the impact of other processes like groundwater, upstream abstraction, glacier melts, etc (as discussed above) and to focus our analysis on sub-decadal drought events within the GRACE period. The smoothed and detrended precipitation anomaly is then integrated in time to get storage anomaly, which is termed as cumulative detrended smoothed precipitation anomaly (cdPA). Finally, cdPA is compared with the smoothed and detrended storage anomaly (dTWSA).

An ecosystem may behave differently under stress (a deficit period) than under an excess-water situation. In this study, the storage (dTWSA) and precipitation (cdPA) linear relationship has been analyzed only during historical deficit periods as the system behaves differently under stress (Famiglietti et al., 1998; Vereecken et al., 2007). Several researchers used a rainfall-runoff curve like soil conservation service curve number (SCS-CN) for the computation of surface runoff based on precipitation with an assumption of stable relation between rainfall and abstraction (Mishra et al., 2006; Singh et al., 2015; Verma et al., 2017). This study also assumes that a pattern of precipitation intensity for a region does not change significantly over time, consequently, the relationship between precipitation and storage variability can be considered stable.

Figure 2 shows the strength of this relationship by correlation coefficients in the top panel and linear regression coefficients in the bottom panel. Based on the linear relationship between dTWSA and cdPA the required precipitation has been estimated. Regression coefficients greater than 1 means the required precipitation is more than the amount of missing water. This is because precipitation lost in other hydrological processes like evapotranspiration, runoff (Eq.1) is not observed by storage variability). Coefficient equals to 1 means the amount of required precipitation is the same as that storage loss, which means there is no other dominant process in the region. Coefficient less than 1 are the regions of weak precipitation-storage coupling, which can be due to other physical processes like melting of snow/frozen surfaces, groundwater extraction, irrigation, etc (non-red regions in Figure 2a) and hence the relationship between storage and precipitation is not strong in this region. Figure 2b shows that for most of the tropical and subtropical regions, required-precipitation is more than the amount of missing water (i.e., regression coefficients greater than 1). For higher latitudes, mass loss observed by GRACE during spring snowmelt is not directly linked to precipitation. Additionally, highly arid regions also have weak precipitation and storage signals and eventually, their coupling is weak. Therefore, the proposed method is not suitable for regions with weak precipitation-storage coupling. These regions of the weak association are identified based on regression coefficients below 1 (Figure 2b), as less than one or negative relationship between storage variability and precipitation may describe a case in which storage variability is not linked to a direct precipitation effect. Also, locations having less than five months of drought in 15 years are excluded because we don't have enough drought samples to derive their association. These regions are considered as unsuitable for the GRACE based recovery analysis and have been masked out in this study.

Figure 2

Based on the derived linear relationship between cdPA and dTWSA, a required-precipitation is estimated for each regional drought period. The method for the estimation of required-precipitation is shown in Figure 3 at an example location (133.75°E 16.75°S) in Australia. The top panel shows an agreement between cdPA (black plot) and dTWSA (red plot). In the bottom panel, an absolute required-precipitation (Figure 3b, blue plot) is calculated by adding precipitation climatology to the estimated surplus required-precipitation (magenta plot), to fill the storage deficit (green plot). Analogous to an accounting methodology, this approach applies the assumption that generally more precipitation than usual (climatology) is required to replenish the losses incurred during drought. The example location has a strong annual signal (5 - 150 mm, with predominantly winter rain) which led to a relatively high ratio of required-precipitation to the amount of missing water.

Figure 3

3.3 Historical Precipitation analysis

Historical precipitation data from GPCP (1979 to 2017) are statistically analyzed using signal decomposition in order to create a simplistic precipitation forecast. Note that the motivation for providing a precipitation forecast here is not to present a state-of-the-art precipitation prediction, but to demonstrate the potential utility of the terrestrial water storage deficit in determining required-precipitation and estimating a likely time to recovery. This methodology could be augmented with any type of more complex precipitation forecasting approach.

3.3.1 Precipitation signal decomposition

Historical precipitation data is decomposed into a linear trend, inter-annual signal, annual/climatological cycle, and sub-seasonal components in order to explore temporal variability. First, a linear trend and an annual signal (mean of each month, e.g., all January, February, etc.) are extracted from the original signal. Then, the residual signal is filtered by a 12-month low-pass window to split it into a smooth inter-annual signal and a high-frequency sub-seasonal signal. The linear trend and inter-annual signal together are considered to contribute to long-term variability. The individual variance of the annual, long-term, and sub-seasonal signals is normalized by their sum, in order to get their fractional contribution to local variability (Figure 4). This provides an overview of the relative importance and spatial distribution of these components in global temporal variability. Figure 4 shows the fractional variance of the decomposed signal. For most regions, annual signals dominate in precipitation (Figure 4a). However, regions where the wet season is not explicit in their climatology, high-frequency signal plays a major role, for example in central Europe, eastern Siberia, western N. America, southern Australia, etc. (Figure 4c). Contrarily, the long-term signal obtained by combining linear trend and the inter-annual signal has the least variability globally (Figure 4b). The smooth inter-annual signals are driven by climate indices like El Niño southern oscillation (ENSO), Pacific decadal oscillation (PDO), and the North Pacific mode (NPM), etc. (Özger et al., 2009). The linear trends can be an indicator of change in precipitation intensity or drought at the beginning or end of the analysis period (1979-2017). We acknowledge that drought at the beginning can produce some artifacts in the misinterpretation of a linear trend. We assume that similar linear and inter-annual trends will continue.
Figure 4

3.3.2 Signal reconstruction and forecasting skill

Based on the above findings, we formulate a statistical model for hindcasting precipitation. The annual signal and the linear trend extracted by signal decomposition (section 3.3.1) are directly used for the precipitation reconstruction, with the assumption of the continuation of the similar variability. Further, interannual variability in the precipitation data is added by autoregression for 10-14 months depending on the duration of significant autocorrelation. Finally, the sub-seasonal signal is added, which is obtained from the residual of the inter-annual signal. This high-frequency signal has only 0-3 months of temporal autocorrelation, accordingly, we have limited skill in synthesizing sub-seasonal signals.
Figure 5 shows the precipitation hindcast for January 2016-December 2017 at an example location (56.25°W 27.75°S) in the La-Plata basin. Figure 5a shows that the reconstructed precipitation (red plot) has a good agreement in 2017 with the GPCP observations (black plot) due to the significant contribution of the interannual signal forecast for the first year. However, the reconstructed signal for the second year is predominantly climatology driven with some linear trend. Figure 5b shows the synthesis of the non-climatological signal forecast. The figure shows that interannual autoregression (blue plot) signals have a good association with the observed interannual signal (black plot) until the first 11 months. The sub-seasonal auto autoregression is significant only for two months in the example location. The final hindcast is an integration of a linear trend, climatology, sub-seasonal, and interannual auto autoregression.
The precipitation reconstruction skill is used for a simplistic normal forecast. Further, two additional precipitation scenarios are simulated by adding respectively one and two standard deviations of precipitation to the normal forecast, which is used in probability recovery analysis.
Figure 5

3.4 Probabilistic recovery

Precipitation has the major control on drought dynamics. Knowing the amount of precipitation required to overcome a drought (at any instance and any location globally), presents the opportunity for the estimation of a likely drought recovery period. We can apply a probabilistic approach by using the historical precipitation forecast model to simulate different precipitation scenarios based on the historical distribution of precipitation for each region. Here, we propose three precipitation scenarios: 1) normal precipitation (as described in section 3.3.2), 2) one standard deviation wetter than normal precipitation is assumed as a wet month and 3) three standard deviations wetter than normal precipitation is assumed as an exceptionally wet month.

In order to overcome a deficit due to drought, the ecosystem needs to receive a surplus of water that surpasses the climatological average. It follows that if drier than normal conditions were to persist indefinitely, then a drought could theoretically go on forever. Whenever precipitation is more than the absolute required-precipitation (Figure 3b, blue plot).; the system advances in recovery to its pre-drought state. Based on this hypothesis, we simulated the three scenarios for how long any instance of drought will continue, given the expected three precipitation cases. Note that the scenarios suggest the needed recovery time for normal, wet, and exceptionally wet months, hence providing a minimum baseline for the duration of drought recovery.

4 Results

4.1 Observed recovery time based on GRACE and GPCP observation

In this study, drought is defined by the negative deviation of TWSA from its record-length climatology. The observed recovery duration is measured directly from the storage deficit, as described previously (Figure 1, Thomas et al., 2014). For our approach, we need to know when the observed precipitation is more than the absolute required-precipitation (section 3.2). Figure 6 shows the recovery estimation of all the droughts occurred during 2002-2017 at four random example locations: Northwest tropical Australia (123.25°E 17.75°S), Northeast Argentina in La-Plata basin (56.25°W and 27.75°S), North India in Ganges Basin (78.75°E and 27.75°N), North Brazil in the Amazon basin (57.25°W and 2.25°S). Whenever the observed precipitation (Figure 6, red plot i.e. GPCP) is larger than the required-precipitation (blue plot) for its respective month, the drought should end. Ideally, GRACE should also observe it simultaneously.

Figure 6

The figure shows that the precipitation during a drought typically stays below its monthly required-precipitation until the end of the drought. In most cases, precipitation crossed the required-precipitation limit in precisely the same month when GRACE observed the end of storage deficit. Even for the case of recurring droughts with two or more months gap, both methods observed the end of drought on approximately the same month. To examine our method in detail we randomly selected a drought month and validated our approach and estimated the recovery time based on different precipitation scenarios in the following section.

4.2 Example of storage deficit and required-precipitation

In this section, we discuss drought in an example month of January 2016. During the study period (2002-2017), the year 2015-2016 was the strongest El-Nino on record, and many regions experienced drought. Nevertheless, it is for the demonstration of recovery analysis and can be applied to any other time window. Figure 7 shows the regions under drought in January 2016 (Figure 7a) and the estimated required-precipitation to overcome the drought (Figure 7b).

Here, the severity of a drought defined by the amount of water shortage in a month. All colors other than white in the figure are drought-affected regions in January 2016, within the region of strong precipitation-storage relations (discussed in section 3.2). The color bar demonstrates the severity of the drought, i.e., the amount of missing water (top panel) and the respective amount of required-precipitation (bottom panel). Figure 7a shows the eastern Amazon, southern Australia, south-east

Africa, and north India were under severe drought in the 2016 winter. For most of the region in the southern hemisphere amount of required precipitation is double the storage deficit because January is a summer month and water demand is higher.

Figure 7

4.2.1 Validation

To validate our approach, we compared recovery periods in Figure 8. The figure shows the recovery period from the January 2016 drought state, observed by GRACE (Figure 8a), and estimated recovery based on absolute required-precipitation and GPCP observations (Figure 8b). Figure 8c highlights the consistency in the estimated recovery period where one indicates a 1– 2 months difference, 2 indicates 3–4 months difference, 3 indicates 5–8 months difference, and 4 indicates 9+ months difference. The black area in figure 8c is the region with extremely different recovery estimates. For the January 2016 drought, approximately 80% of the masked global land area demonstrated a similar recovery period (+/- 1-2 months) to what was predicted (category 1 in Figure 8c).

Figure 8

4.2.2 Precipitation scenarios

This section demonstrates the probability of recovery duration in different precipitation scenarios. In the first section, we talk about the expected recovery percentage within a month in three different precipitation scenarios. And in the second section, we projected the duration needed to overcome the January 2016 drought within the study period (until March 2017).

4.2.2.1 The expected one-month recovery state

Spatiotemporal patterns of drought at the global scale are largely uncharacterized. Often, one-month of surplus precipitation is not enough to fill the entire deficit. However, if it rains significantly above average immediately after/during the drought, the recovery time decreases dramatically. Therefore we compared three different surplus precipitation scenarios (discussed in section 3.4) to estimate recovery percentage for the January 2016 drought. The surplus precipitation within a month (February 2016) is divided by the required reconstructed precipitation to calculated percentage recovery. In most of the drought-affected regions, the recovery percentage of our forecasted normal precipitation (section 3.3.2) for February 2016 is more than the recovery percentage of observed GPCP precipitation (Figure 9d). This indicates, February 2016 was drier than our estimated normal. Most of the region recovered in extremely wet scenarios (Figure 9c) within a month, except, regions dominated by summer monsoon (Figure 9c, blue/cyan colored area) with less than 30 % recovery, as February is not a rainy season for this region. This shows a case that regions with high amplitude seasonal cycles in precipitation mostly recover during their rainy season, which varies globally.

Figure 9

4.2.2.2 Best estimated time for recovery

Recovery time varies from immediate (i.e., one month) to several years across different climate zones and depending on the severity of the drought. Figure 10 shows the predicted recovery duration of the January 2016 drought state, which ranges from a month (yellow color) to not recoverable within the study period of 15 months (black color). Figure 10d shows the recovery duration observed by GRACE, which is considered as truth. Figures 10a & 10b show that most of the region under severe drought in 2016 did not recover with even one standard deviation wetter than normal precipitation and the drought in this region continued beyond a year. In the extremely wetter (three standard deviations) than normal situation (Figure 10c) most of the regions recovered within 4-5 months, except for regions of most severe drought, such as the South East Amazon, and Southern Africa. Even in the extremely wet scenario, the monsoon regions (Figure 10c) recovered only during their rainy season (in 6-7 months from January 2016). This demonstrates that information on the state of precipitation compared to its usual can provide an idea of the expected drought recovery duration provided we know the amount of precipitation required.

Figure 10

5 Discussion

Here we define drought intensity and duration using the observed storage deficit from GRACE TWSA, which is a 3-months or greater negative deviation from the historical, record-length climatology for each region, following Thomas et al. (2014). Generally, we considered this to be a better metric of integrated drought effects than a negative departure from climatology in precipitation or soil moisture because the former includes all components of the water cycle and represents the integrated state of the local water budget closure, dS/dt. We observe that occasionally precipitation anomalies are depressed a couple of months before GRACE sees the beginning of drought onset because the net water mass balance can stay stable for some time by a compensating decrease in ET and runoff. Similarly, precipitation shows a positive deviation from climatology (i.e., excess precipitation) well before GRACE observes the end of the drought because of the time-lag to fill the rootzone soil moisture (Eltahir and Yeh, 1999). (Dettinger, 2013; Maxwell et al., 2013) also argued that drought onset is quicker than drought termination. Sometimes very heavy rain can quickly bring a region entirely out of a drought, but in many cases, continuous surplus precipitation is needed to bring the entire water column (i.e., from the surface to groundwater) to fully recover.

The critical feature of the GRACE-based drought recovery framework is the estimation of required-precipitation to fill a storage deficit. Figure 2 shows that TWSA is closely associated with cumulative precipitation anomaly for most regions, except in deserts and high-latitudes. In large arid regions, monthly storage variability is significantly low due to low rainfall. In high-latitudes, seasonal water storage variability is mainly driven by temperature because of snow accumulation and melt. Typically in cold regions, winter snow accumulation and spring snowmelt drive increases and declines in TWSA, decoupling the storage variability from precipitation variability, which leads to a phase shift in their seasonality and weak correlation between them (Reager and Famiglietti, 2013). For these reasons, a storage-based drought recovery metric is not as capable in desert and high-latitude areas and are masked out in the results section.

Variability in the historical precipitation data is analyzed by signal decomposition to develop a simple precipitation forecast model. Precipitation signals are hindcast by combining the climatology with the linear trend and an interannual signal estimated from autoregression. Figure 4 shows that in most regions seasonal variability is the strongest signal, except in big deserts, Eurasia, and northwest America. These regions have high sub-seasonal variability in precipitation, which is hard to reconstruct. Additionally, due to the contribution of snowfall in higher latitudes, and very low rainfall in deserts, bias correction in precipitation data are relatively less reliable. Consequently, we have less confidence in precipitation simulations in those regions.

In addition to the normal precipitation forecast, two more precipitation scenarios are simulated based on one and three standard deviations from the climatology, assuming that a system recovers from drought only when the precipitation is more than the usual (climatological) precipitation of the corresponding month. Figure 9 demonstrates percentage recovery given these three different precipitation scenarios. The figure shows that most regions show significant recovery within a month in three standard deviations wetter than normal scenario, except for regions that are not in their respective rainy season. As precipitation can be scarce in non-rainy-season months, even three standard deviations wetter than the historical average precipitation would not be a substantial amount of rain to replenish the water deficit in these periods. We further investigate the recovery duration based on different precipitation scenarios (Figure 10) and find that under normal precipitation, most regions will not recover significantly within the study duration, but for three standard deviations wetter-than-normal rain, they recover within 3-4 months. However, for the regions with the strong seasonal precipitation intensity (monsoonal region), the figure showed recovery only during its rainy season (after 6-7 months) even in the extreme wet scenario.

We validated our required-precipitation estimates by comparing the recovery period observed by GRACE and estimated by our method on the GPCP observations (Figure 7) at different locations, which showed good concurrence. Also in Figure 10, the drought recovery duration for an example month of January 2016 demonstrated a good agreement between the observed recovery by GRACE and estimated recovery by GPCP for most of the masked regions (80% within +/- 1 month).

Knowing the present state of precipitation, i.e., how much surplus we have over usual climatology of a region can give an idea of expected recovery duration, provided we know the amount of precipitation needed to fill the deficit. With the improved precipitation forecasting skills, more accurate drought recovery estimates can be obtained. Nevertheless, the study demonstrates a case of application of GRACE for the estimation of required-precipitation for drought recovery.

6 Conclusions

Increasing water-demand and future uncertainties in climate necessitate the assessment of the potential impact of drought and its expected recovery duration. The consequences of drought can be minimized through adaptation and risk management efforts, informed by the amount of missing water in a system and required-precipitation needed to bring it back to normal (as shown in figure 7). Recurring droughts due to insufficient recovery can be minimized to a large extent by managing water resources wisely particularly during the deficit period until all of the hydrological components revert to the pre-drought state. The study demonstrates the utility of GRACE terrestrial water storage anomalies (TWSA) in obtaining statistics of hydrologic drought, i.e., its recovery period and required-precipitation to recover with sensitivity test to different precipitation scenarios. The benefits of the GRACE-based drought index for drought analysis are: 1) the independency from meteorological variables unlike other drought indices (PDSI, SPEI, SPI) and 2) the spatial coverage of the GRACE data (much of the globe). However, recovery analysis is limited to the area where linear-relationships between TWSA and cumulative precipitation anomaly exhibit strong linkages. However, careful cautions are warranted to interpret the GRACE signal at 0.5 degree grid due to different post processing techniques applied by different GRACE solutions to overcome the inherent limitation in the spatial resolution of GRACE. Significant difference in the intensity of drought is observed by different GRACE solutions. Nevertheless, all GRACE solutions have the same drought durations.
The findings of this study are 1) the GRACE based drought index is valid to estimate the required-precipitation for drought recovery and 2) the period of drought recovery depends on the intensity of precipitation i.e. in the dry season of the year drought continues even with above-normal precipitation. The recovery period estimated by our approach matches well with the recovery observed by GRACE for most of the masked regions (80%) for the demonstrated drought month. This approach can be extended with the availability of new GRACE follow-on (GRACE-FO) datasets, launched in May 2018. The proposed method and analyses in this study are applicable to the development of an operational drought monitoring system that can provide actionable information for drought recovery, provided the skillful precipitation prediction is available.

Funding: This research was funded by the GRACE science team meeting.
Acknowledgments: The research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D004).
Conflicts of Interest: The authors declare no conflict of interest.
Author Contributions: For this research article Dr. Singh has contributed in data curation, formal analysis, writing, and visualization. Dr. Reager has conceptualized, supervised, and acquired funding to conduct this study. He has also helped in writing and editing the text. Dr. Behrangi has also contributed by supervision and funding acquisition.

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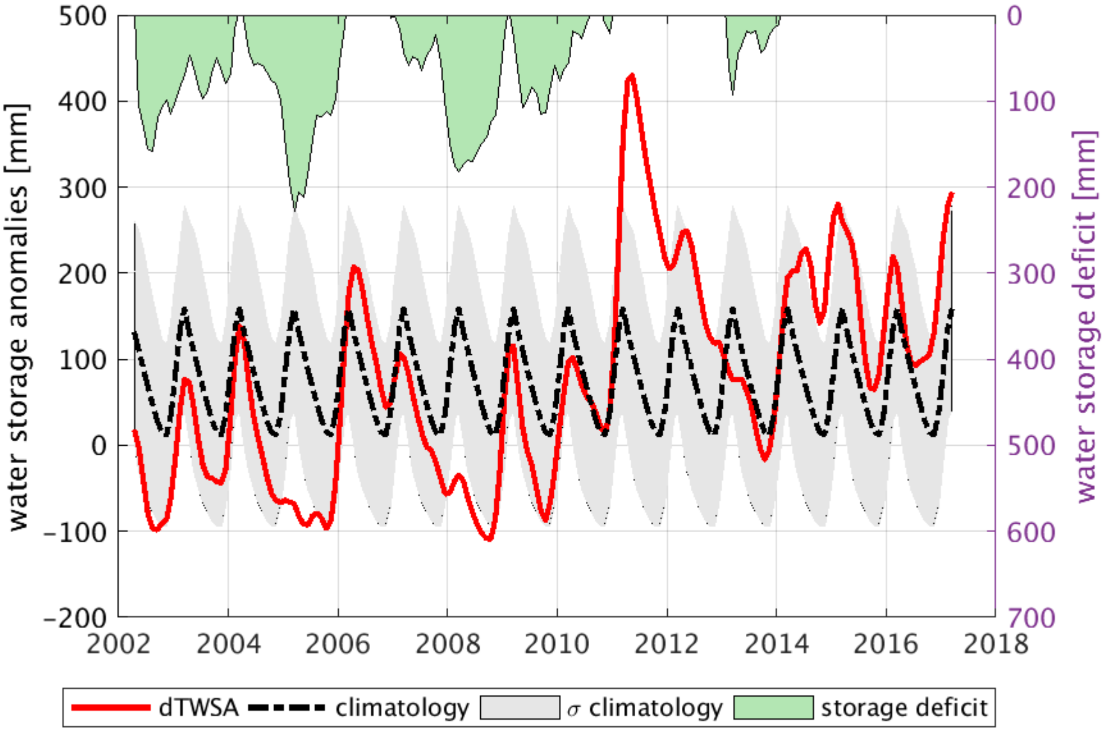
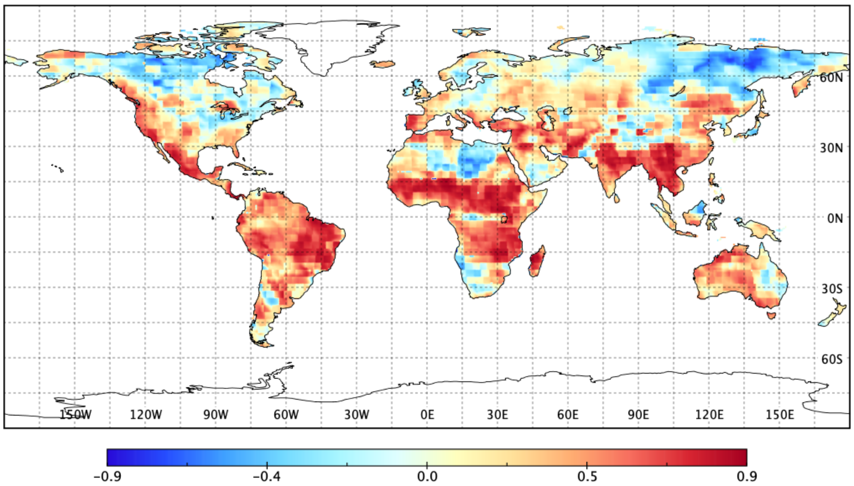


Figure 1: Water storage deficit from GRACE: The smoothed and detrended TWSA (dTWSA in red plot) is reduced by its climatology (black plot), to estimate deviation from the climatology. The negative residuals from the climatology are plotted on the upper axis as a green shaded area and scaled on the right side. The grey shade indicates ±1 standard deviation of the climatology.

a. Correlation coefficients



b. Regression Coefficients

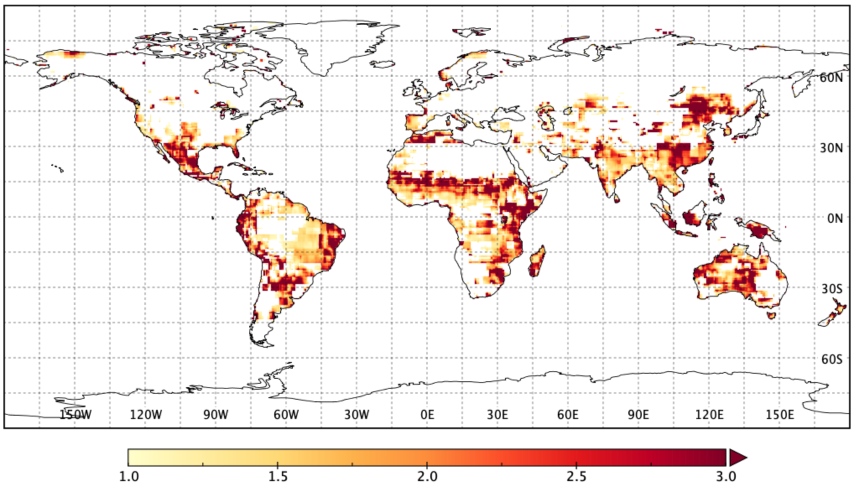
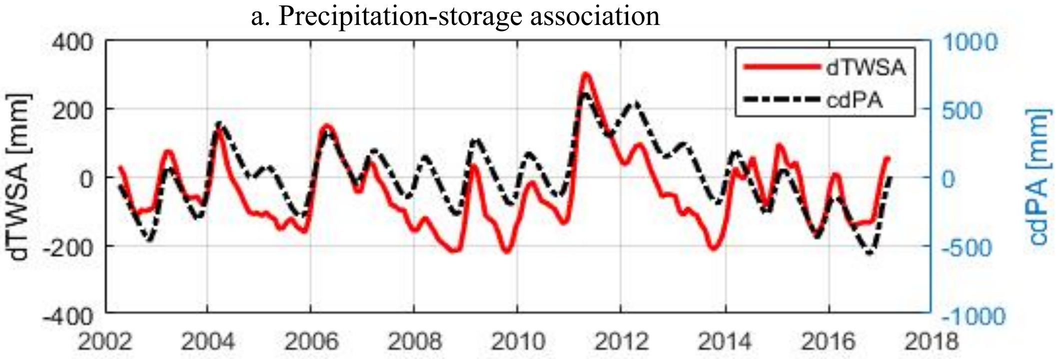


Figure 2: a) Correlation coefficients and, b) regression coefficients between cumulative detrended precipitation anomalies (cdPA) and detrended terrestrial water storage anomaly (dTWSA).


a. Precipitation-storage association

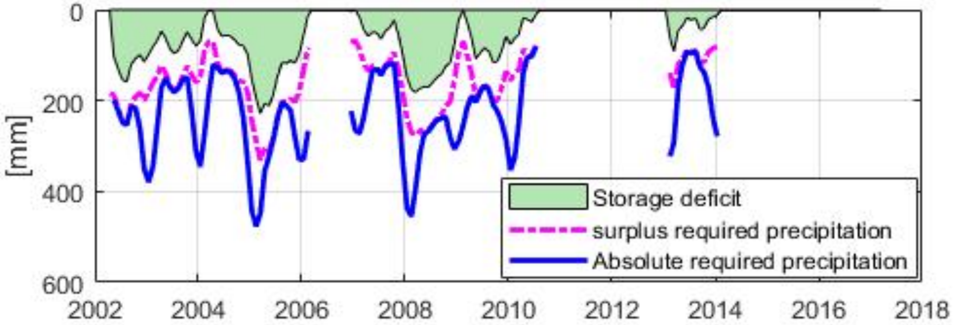
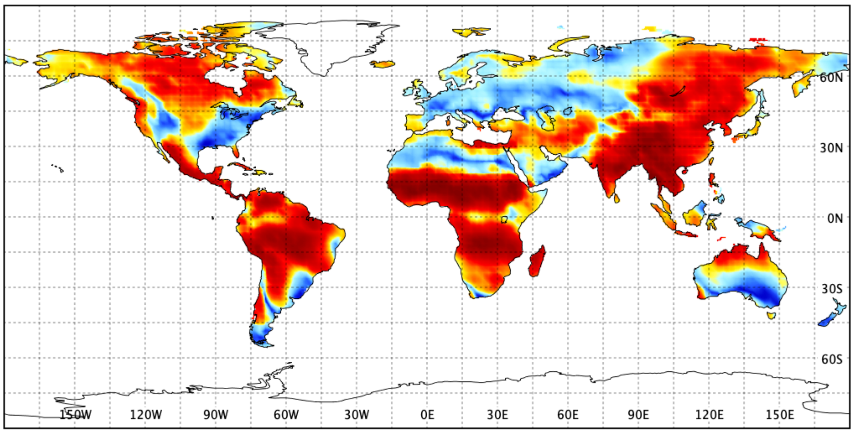
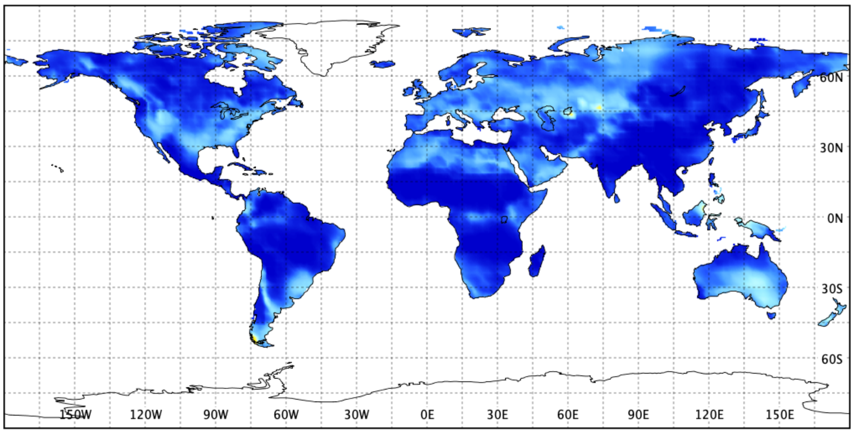

b. Estimation of required-precipitation

Figure 3: Estimation of the required-precipitation at an example location. a) Cumulative detrended precipitation anomaly (cdPA) compared with the detrended storage anomaly (dTWSA). b) Surplus required-precipitation is estimated (magenta plot) from the linear relationship between dTWSA and cdPA, to fill the storage deficit (green plot). Then precipitation climatology is added to obtain absolute required-precipitation (blue plot).

a. Annual Signal



b. Linear trend + inter-annual signal



c. Sub-seasonal signal

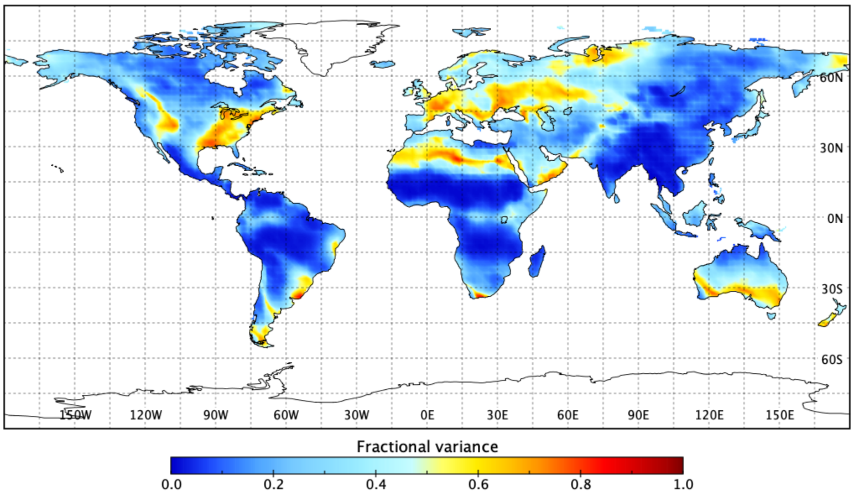
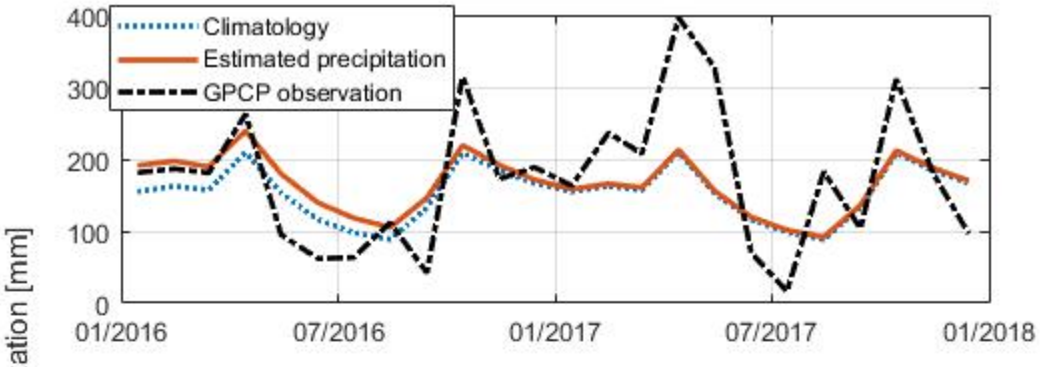


Figure 4: Fractional variance of the decomposed signal to the full signal. a. Annual Signal, b. Long-term signal, c. sub-seasonal high frequency signal

a. Improvement over climatology



b. Reconstruction of non-climatological signals

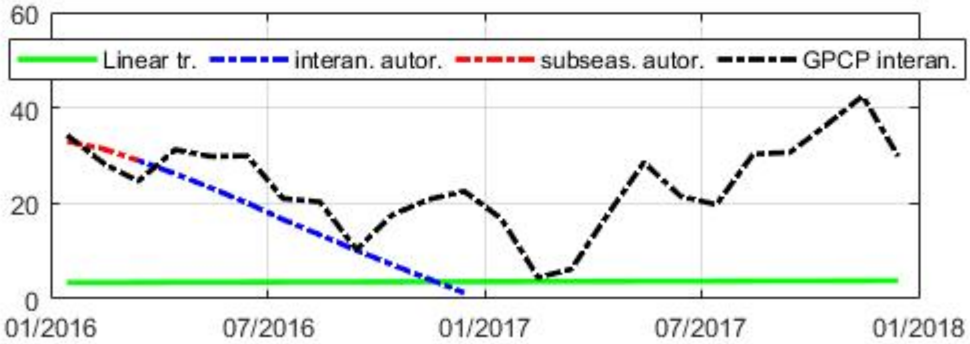
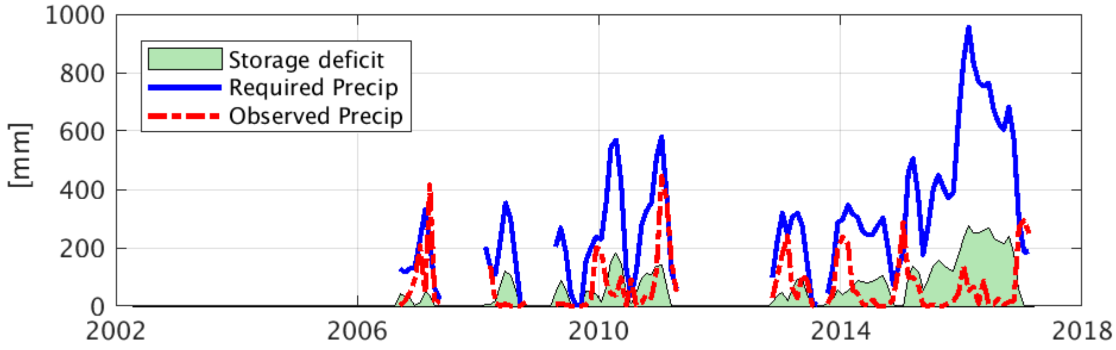
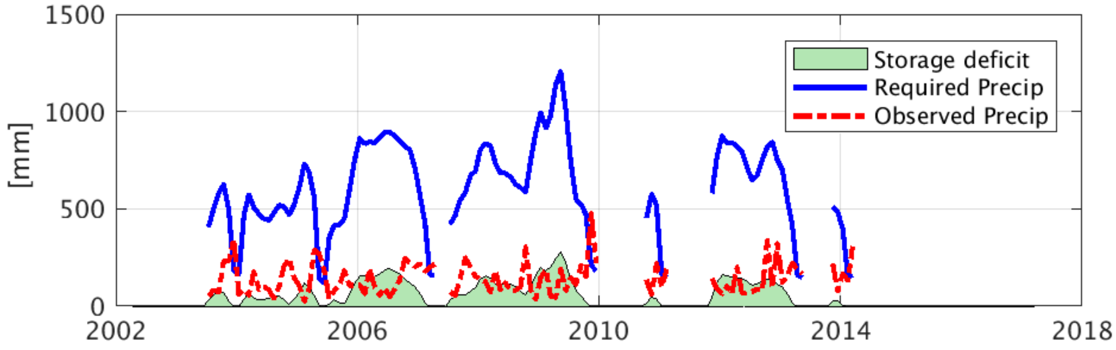


Figure 5: Reconstruction of precipitation signal for 2016-2017. a) The reconstructed signal compared with GPCP observations and its climatology. b) The reconstruction of a long-term secular signal from the linear trend, and inter-annual and sub-seasonal autoregression, compared to GPCP interannual signal.

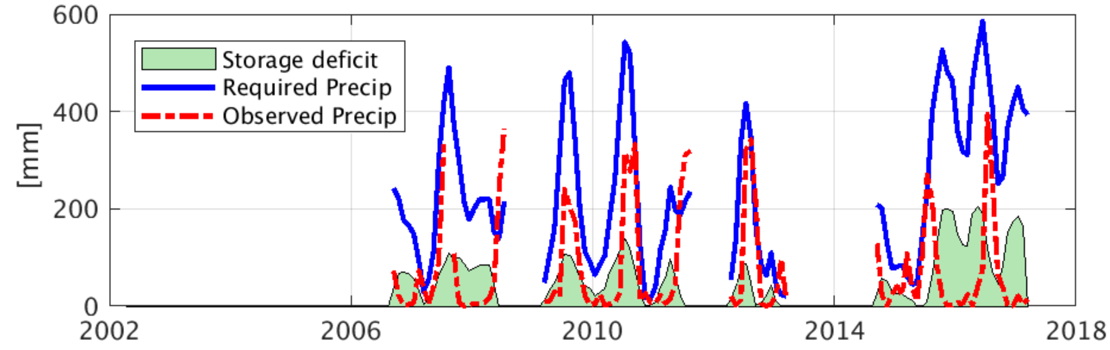
a. NW Australia



b. NE Argentina



c. N India



d. N. Brazil

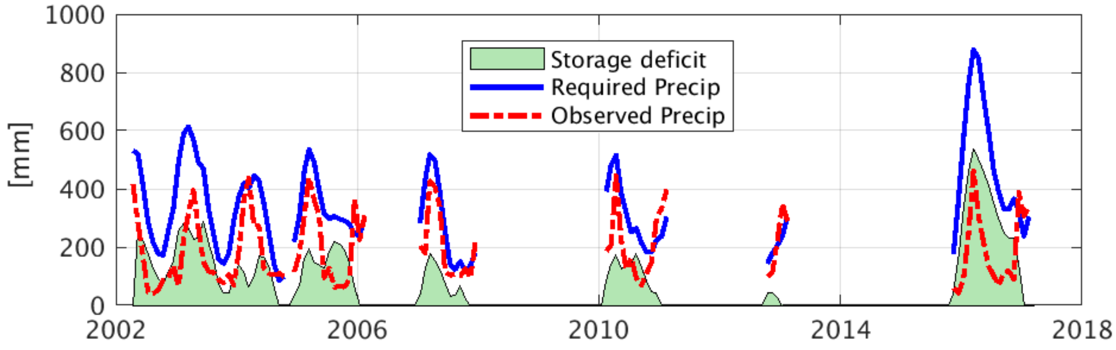
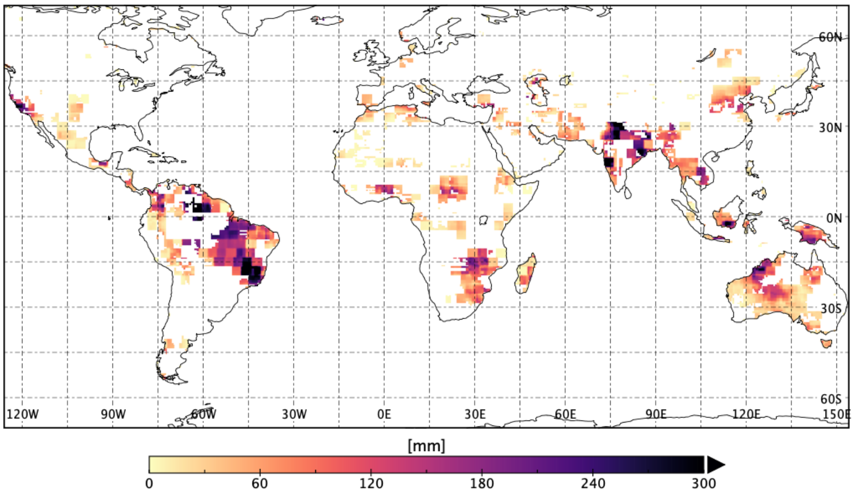


Figure 6 Validation of the required-precipitation estimate by drought recovery estimates at example locations. The different instances of drought show that drought ends (from the perspective of TWSA) whenever observed precipitation (red plot) exceeds the required-precipitation (blue plot).

a. Storage deficit



b. Required precipitation

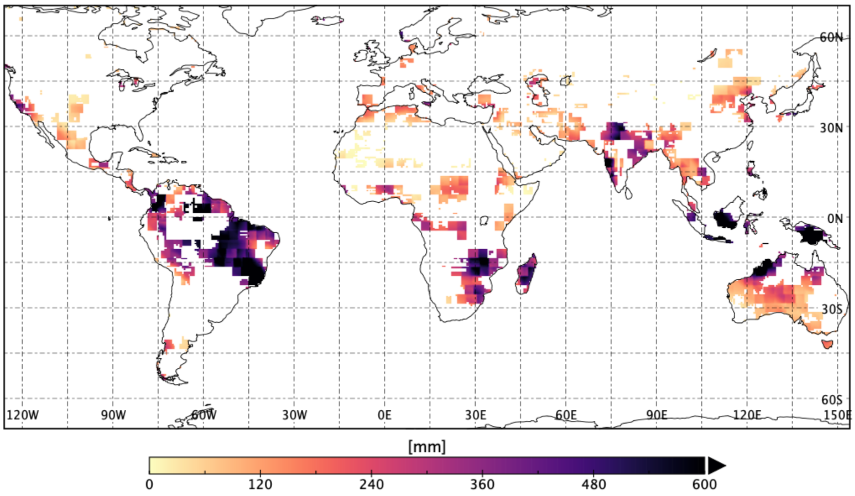
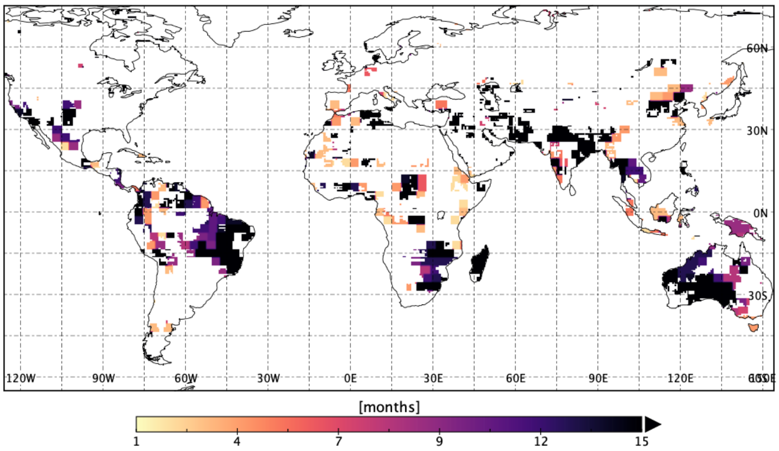
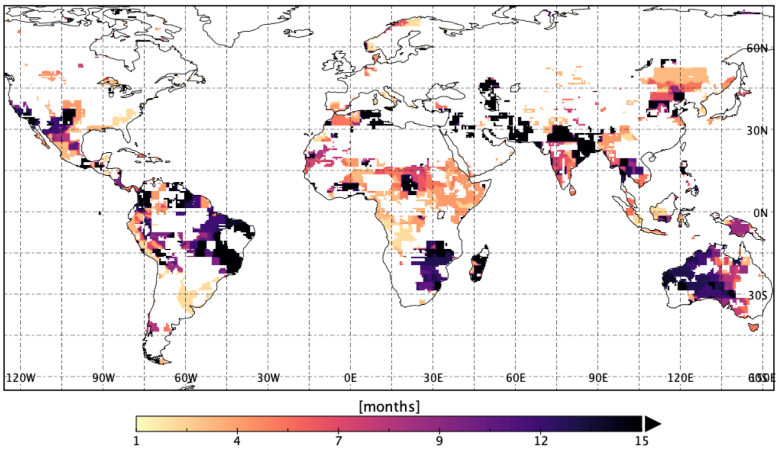


Figure 7: a) Storage deficit in an example month (January 2016). b) the amount of required-precipitation to fill the deficit.

a. Recovery period observed by GRACE



b. Recovery period estimated by the discussed method



c. Consistency in the recovery estimates

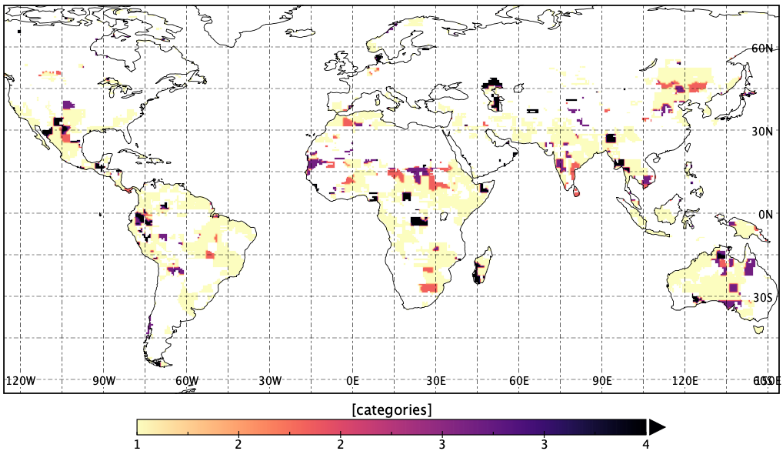
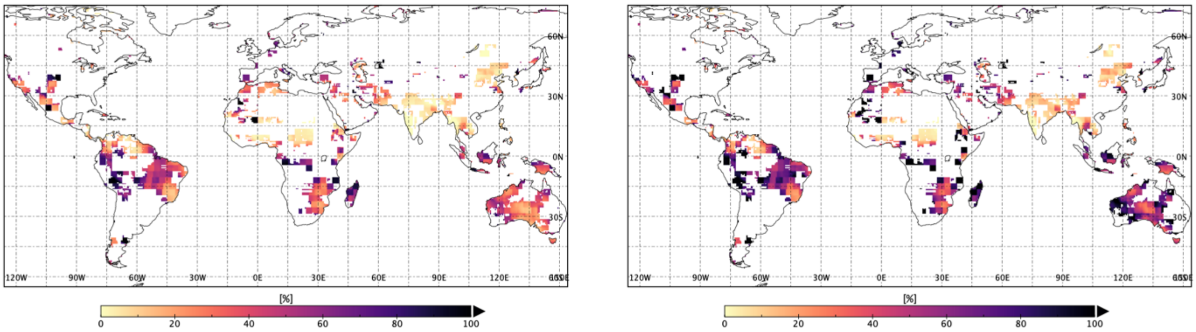
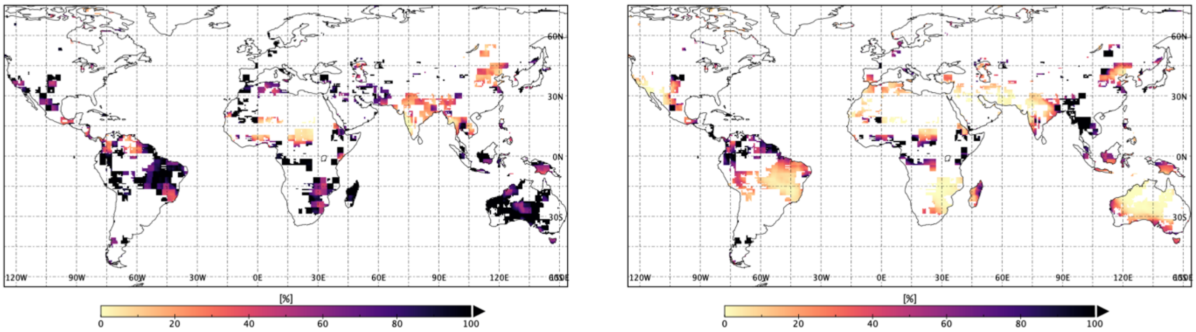


Figure 8: Validation of the estimated required-precipitation by the recovery duration from January 2016 drought observed from: a) GRACE and b) estimated by the discussed method using GRACE and GPCP observations (middle panel). c) consistency in the observed recovery duration by GRACE and GPCP (1 = 1-2 months difference, 2 = 3-4 months difference, 3 = 5-8 months difference and 4 = 9+ months difference).



a. Normal precipitation

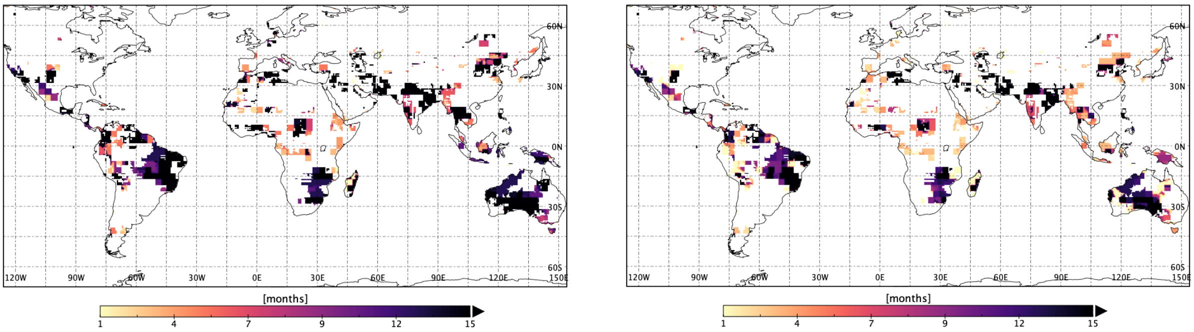
b. 1 std. wetter than normal



c. 3 std. wetter than normal

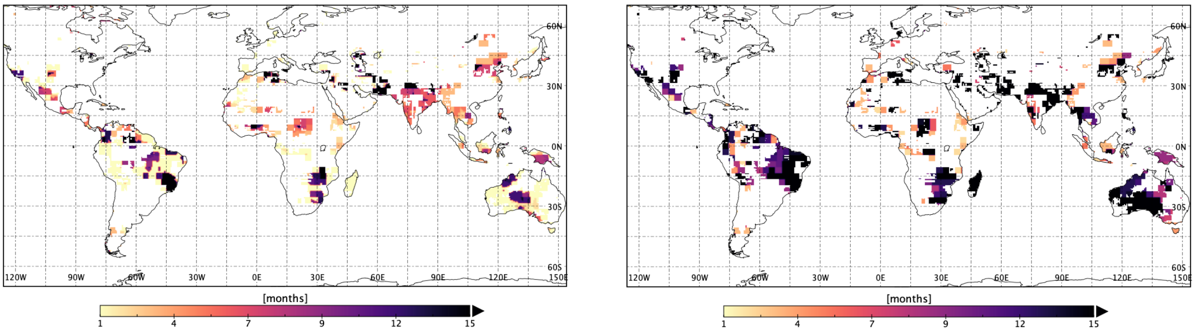
d. Observed (GPCP) precipitation

Figure 9: Expected percent recovery in a month given the three different precipitation scenarios and the observed GPCP precipitation.



a. Normal precipitation

b. 1 std. wetter than normal



c. 3 std. wetter than normal

d. Observed recovery duration by GRACE

Figure 10. Duration of drought recovery from January 2016, given the three different precipitation scenarios and as observed by GRACE