We are grateful for the detailed and careful review of our work by the three referees and the Editor Prof. . The following lists the responses to these comments and suggestions. The resubmitted manuscript has been corrected and improved accordingly.

Comments by Prof. Qiang Zhang

SC1: Water is one of the critical resources to sustain the rapid socioeconomic development. Vegetation cover is high and most of them is evergreen subtropical species, which means there could be substantial water consumption by plants throughout the year given the favourable climate. Water and ecological management faces increasing challenges because of the rapid population growth, high urbanization and industrialization, etc. Therefore, this is a timely study to investigate the intensive changes and interactions between vegetation and water. The most interesting part of this study, to me, is the identification of the 'hotspot' of changes and determination of water-limiting-vegetation even in this rainfall-abundant region. The m/s is well structured, the wordings are fine, and method/analysis are appropriate. In my view, this study is meaningful and worth publishing. Having said these, I do still have a few concerns listed below for the authors to address:

Thank you for the encouraging comments. The concerns are addressed below.

SC1: 1. I find the summary of the water-plant relationships in Line 61-69 is quite interesting. Vegetation consumes water and causes reduction in water resources on the one hand, and water availability will restrict vegetation establishment and growth on the other. Indeed, plant-water relations are examined mostly in arid and semi-arid regions for the purpose of water and ecological conservation. Are there such studies in humid and semi-humid regions investigating the controlling factors – energy vs. water - of vegetation growth? It is important and is the authors responsibility to ensure a thorough literature review on this subject.

AC: The possibility of different vegetation-water relationships under contrast climate conditions is the motivation of this study.

Most such studies focus on the drylands because of the likely more severe water scarcity and ecological problems, while the plants and water/energy relationships are left less clear in the subtropical wet/humid areas where precipitation and radiation are both abundant. Although there have been studies in humid areas investigating environmental controls on plant water use such as those in the last paragraph of Introduction and Discussion 4.3, they focused on plot/stand scale mainly, or a national scale, and rarely discussed the relationships under contrasting dryness conditions.

SC1: 2. A brief paragraph should be added before Line 74 for an introduction of relevant studies that have been carried out in the Pearl River Basin. Without this, it is a bit out of blue to see the next paragraph suddenly mentioning something in this basin.

AC: Thanks for the suggestion. A short paragraph has been added, please refer to Line

78-89 in the revised version, and the Study area section 2.1 has been edited accordingly.

SC1: 3. Regarding the data: I see a comparison between GLDAS precipitation and the ground truth data over a number of pixels given in Fig. 11. GRACE data from different processing centers are also compared. No comparisons/discussions are given for ETp and other variables. Can you find some studies in this basin or a basin with similar vegetation cover and climate that use GPP from MODIS? If there is any, it'd provide more confidence in the results of this study.

AC: Data uncertainty is always a big concern especially when remote sensing and modelling results are involved. In this submission, we have obtained ETp and GPP from more common sources and provided more comparisons to discuss the data uncertainty. The comparisons are given in a supplementary document and referenced in the main text. Please refer to Section 2.2 *Data sources and pre-processing*, and section 4.1 *Uncertainties in the datasets and results*.

SC1: 4. The current m/s is a complete story by overlooking the water-vegetation relationships in the entire basin in space and time. It is good to locate the hotspots of changes and interactions because these areas would usually be the 'focus' of land/water management and for risk control, etc. I recommend the authors to take a further step to investigate the reasons behind the changes and interactions right in these hotspot areas.

AC: Thanks for the comment and suggestion. The main purpose of this study is to examine the relationships between vegetation parameters and hydroclimates, especially under contrasting atmospheric dryness conditions. Through the analysis, we found the areas of croplands where vegetation parameters and hydroclimates changed greater than other areas, and presumed that the relationship in these areas is possibly related to agricultural activities like irrigation and planting structure change, etc. We screen this hotspot area out in another work to investigate in depth what drives the intensive changes of vegetation index and productivity in these areas. For that we are still collecting agricultural data including planting structure, crop yield, cropland area, irrigation and fertilization areas, etc. They are not incorporated into this study.

SC1: 5. Paragraph ends with Line 279: This is a good argument that vegetation relies on water because of the lags of vegetation parameters after water input & storage dynamic change. However, there seems a lack of support to the opposite standing, i.e. vegetation growth does not result in excessive water reduction. So this part of discussion needs a further expansion.

AC: From the phase shift between water (P & TWS) and vegetation growth at the monthly scale, we concluded that water limits vegetation growth in this region because the latter varies following the change in the former. The opposite possibility, i.e. vegetation water uptake leading to storage reduction cannot be detected at the investigated time scale but might be more evident at a shorter time scale like sub-daily in Kirchner et al., (2020) and Shen et al., (2015), who found decline in groundwater level/soil water content with increase in sap flow rates. Statement has been given in the relevant location in the text (Line 354-357).

Kirchner, J., Godsey, S., Osterhuber, R., McConnell, J. and Penna, D.: The pulse of a montane ecosystem: coupled daily cycles in solar flux, snowmelt, transpiration, groundwater, and streamflow at Sagehen and Independence Creeks, Sierra Nevada, USA, Hydrol. Earth Syst. Sci. Discuss., 1–46, doi:10.5194/hess-2020-77, 2020.

Shen, Q., Gao, G., Fu, B. and Lü, Y.: Sap flow and water use sources of shelter-belt trees in an arid inland river basin of Northwest China, Ecohydrology, 8(8), 1446–1458, doi:10.1002/eco.1593, 2015.

SC1: 6. Fig. 2-5, 7: the spatial distributions of these variables/trends are shown for all pixels. How would it be like if only the ones with $p<0.05$ are shown?

AC: Trends of some variables are not statistically significant. We have marked the pixels with significant trends for NDVI and GPP in Fig. 4-5. The correlation coefficient with $p<0.05$ is also marked in Fig. 7.

Anonymous Referee #1:

RC1: The manuscript evaluates regional scale plant-water relations in the Pearl River Basin. The authors find a strong inter-annual correspondence between NDVI and GRACE derived TWS, suggesting water limitation in an area where rainfall is generally higher than the potential evapotranspiration. This is an interesting result, but the underlying mechanism remains unclear. The introduction touched on a few important topics such as water limitation and plant water use, but the scientific hypothesis/questions are not clearly defined. "Quantifying the plant-water relations at different temporal scales under different dryness conditions" is a good starting point, but the specific questions to address need to be defined.

The choice of vegetation data needs justification. NDVI is known to saturate in the forest ecosystem. MODIS GPP poorly represents soil moisture limitation on productivity which is directly relevant to the main theme of this study. There are many other vegetation metrics available that are not or less affected by these issues (e.g., SIF and EVI). LAI has also been used in a similar domain (Tong et al., 2018). I suggest the authors adopt these other datasets in the analysis.

The strong inter-annual correspondence between NDVI and TWS is interesting, given how humid this area is. It would be of interest to see if this correspondence changes across different biomes (e.g. crops vs. forests) or regions with different levels of aridity, which may be done at mascon resolution. On the other hand, the monthly-scale correlation analysis needs clarification. Is the trend and seasonality removed from the monthly time series?

The discussion session lacks a clear focus and sometimes reads like a literature review (e.g. Line 280-294). The discussion should be centered on clearly defined research questions and based directly on the results of this study.

AC: We thank you for kindly pointing out the weaknesses for us to further improve the manuscript quality.

In the Introduction, we reviewed studies of plant-water relationships using both field observations and remote sensing across different spatial scales and summarized some general findings of such studies. Further, we stressed that these findings are mostly based on studies in the arid and semi-arid regions, while studies in radiation-sufficient humid and semi-humid regions are still limited. We have restated the specified research objectives and discussed the possible underlying mechanisms (which is still limited based on the analysis) for the relationships from the perspective of energy & water availability in this environment compared to the dry environment. The mechanisms can be obtained with such comparisons but can hardly be verified using the applied data in this study.

We were aware that applying different datasets (for both hydroclimate and vegetation) could lead to a possibly different result, therefore, we gave the reasons of our data choice in *2.2 Data sources and pre*-processing and 4.*1 Uncertainties in the datasets and results*. Choice of vegetation data was based on literature review, that we found GIMMS NDVI3g is among the most popular datasets for analysis of vegetation phenology and its relationship with hydroclimate change, especially for studies in a relatively large river basin as it covers a moderately long time period (since 1980s). Using GIMMS NDVI3g may allow the comparison of this study with many other studies in the region. Considering most of the forests consist of evergreen trees, and forest cover (~65%) nearly remains constant from the early 21st century, the NDVI trend is highly likely induced primarily by other land cover types especially croplands (~18%) and grassland (~9%). From these points of view, we think NDVI is fit for the purpose of this study. Using other vegetation indices like EVI and SIF may result in slightly different values of the trends but the overall changing direction (+/-) may be consistent. As to GPP data, we have added data from VPM and PML in addition to MOD17 products and the comparisons among them are given in section 4.1 and the supplementary document. We found the overall results (spatial distribution, trends and relationships with hydroclimate data) changed little compared to the results based solely on MODIS GPP.

We have also improved the discussion with an emphasis on data uncertainty, hotspots for changes and possible reasons, as well as the interactions in dry and wet conditions.

RC1: Detailed comments:

Lines 72-73. This statement needs clarification. Is it to question if water limitation prevails in the humid ecosystems in the long term?

AC: This sentence has been rephrased as '*While majority of such studies were carried out in semi-arid regions because of the urgent need to find an equilibrium threshold* *between ecological restoration and available water resources in these water-limited areas, it is still largely unclear whether the restriction of water resources or available energy on vegetation growth prevails in the humid or semi-humid areas with both abundant rainfall and radiation*'

RC1: Line 105. I think it is better to define the TWS anomaly using the entire analyzed period as a baseline (by removing the mean calculated over the entire period), unless there are specific reasons to believe that the 2004-2009 period better represents a "normal" condition.

AC: We did not define the baseline period for GRACE data. Actually, GRACE satellite data are released by three processing centres as TWS anomaly, which is the actual (ungiven) TWS value in each month minus the monthly mean from the period of 2004 to 2009. There is a good reason to question the representativeness of this period as 'normal' condition, but with all data relative to the same baseline period, we believe the results will not be affected.

RC1: Lines 129-132. The mean annual TWSA depends on the choice of the reference period. The trend analysis is a better way to illustrate wetting/drying information. Are all the trends significant in Fig 2d?

AC: Refer to the above respones. In addition, the linear trend will not change after subtracting a value from a data series, even if the minuend differs. So the trend analysis is not affected by the baseline period.

The spatial TWSA trends are mostly insignificant, just like its temporal trends. The trend will change with the study period though, for example, if we focus on the period of 04/2003-03/2015, then the linear trend will be 6.99 mm yr^{-1}, with a p value of 0.006. This is mentioned in the Discussion 4.1 starting with Line 293.

RC1: Fig 2e. Please clarify how the basin average and the associated errors (measurement and leakage) are calculated. This should be included in the Method session.

AC: Thanks for the suggestion. We have added information in the 1st paragraph of subsession *2.2 Data sources and pre-processing* and second paragraph in *2.3 Data analysis* as suggested.

RC1: Line 145. What is the trend in space? Note that here the trend in time does not have an error bar.

AC: We have rephrased this sentence as '… with an overall positive trend spatially (0.002±0.009) and temporally (0.005±0.025), …'.

RC1: Figs 3-5. Please change the color scheme to improve the readability of the figures. For example, a sequential colormap is ideal for the aridity index. For the anomaly and trends, it is better to use a diverging colormap with a symmetric scale.

AC: Thank you for the suggestion. We have changed the color scheme accordingly to improve the figure readability. Please refer to the updated figures.

RC1: Line 153. Please label the significant trends in the map.

AC: The NDVI, GPP trend maps have been reproduced with pixels of p<0.05 marked with crosses. So has the figure for correlation coefficients of annual data.

RC1: Lines 159-161. This reads like discussion, not actual results.

AC: We have carefully checked the results and moved the discussion-like contents to Discussion.

RC1: Lines 169-170. Needs other proxies for plant productivity to confirm this. MODIS GPP directly accounts for the limitation from VPD but not from soil moisture supply.

AC: Thank you for the suggestion. Indeed, MODIS GPP alongside many other GPP products does not account for moisture constraint but rather atmospheric controls including temperature, VPD and radiation. In our study area, rainfall and water storage is high in the growing seasons (conventinally defined as April to October) and slightly lower in the nongrowing seasons. In this case, the moisture restriction on GPP might be small. In addition, we compare GPP from three sources (MODIS, VPM and PML) in the supplementary figures, and we used the mean GPP values of the three products in the this submission. Session 2.2 regarding data sources and session 4.1 regarding data uncertainty are extended to incorporate this content.

RC1: Fig 7. Please either label the areas with significant correlations or mask the insignificant ones. Trends can inflate the correlation results. Have you de-trended the time series?

AC: Linear trends are removed before the correlation analysis. This information has been added in the Method session (Line 159). Thanks. Fig. 7 has been updated with crosses marking the significant correlation coefficients.

RC1: Line 182. It is unclear how the monthly scale regression is calculated. Note that to quantify water limitation, the seasonality should be removed from the monthly time series.

AC: Information has been added in the Method session (Line 159). Data were detrended before calculating the correlation coefficients.

RC1: Lines 189-190. It is unclear what this means. How are the water restriction and water consumption quantified and compared? In fact, quantifying the amount and timing of plant water consumption (e.g. ET in wet and dry years) might be helpful to understand why there is an apparent water restriction in such a humid area.

AC: This sentense has been rephrased (Line 233-235). We assume that vegetation growth is constrained by water resources if dynamics of NDVI/GPP falls behind dynamics of P/TWSA (Line 164-167). The degree of constraints of dryness and water on vegetation is implied by the corelation coefficient in Fig. 6-7 and Fig. 10.

RC1: Line 196. How is the span of the growing season defined in this area?

AC: Growing season months have been given at their first appearance in section 3.3 (Line 241 & 246). Because it can vary from year to year for each type of vegetation cover, we use the conventional definition in this study, i.e. from April to October. Precise quantification of growing season length can be done with vegetation index time series but won't be necessary for this study.

RC1: Lines 212-220. This should go to the Data and Method session.

AC: We have provided comparisons of P, ETp, GPP from multiple sources in the section 2.2, and extened the discussion of data uncertainty in section 4.1.

RC1: Line 230. The uncertainty of the trend needs to be evaluated.

AC: The uncertainty of the temporal and spatial trend analysis throughout the text and figures has been defined. Please refer to the updated submission.

RC1: Lines 232-241. This should go to the Data and Method session. The authors present examples where MODIS GPP shows consistency with other vegetation data, but in thisstudy, the analysis based on the two datasets (MODIS GPP and NDVI) shows different plant-water relations. It is unclear if the difference is physical (e.g. due to the different responses of vegetation state and vegetation productivity) or caused by data accuracy issues. In this case, other vegetation metrics are needed to justify the results.

AC: In this submission, we used multiple datasets to reevaluate the relationships between vegetation and hydroclimate, and found that using the ensemble means of multiple datasets did not lead to significant difference in the results compared to the last submission. In addition, we noticed that GPP algorithms for MODIS, VPM and PML are all formulated with atmospheric variabels like temperature, VPD and radiation. It is found there exists time lags between these atmospheric conditions and NDVI, therefore, the NDVI and GPP should not synchronized in temporal dynamics, which would result in different response characteristics. This has been added in Discussion 4.3 (Line 334-339).

RC1: Line 257. Note that this is an active area for ecological restoration, including the Grain to Green project (Tong et al., 2018). Reference: Tong, X., Brandt, M., Yue, Y., Horion, S., Wang, K., Keersmaecker, W. De, : : : Fensholt, R. (2018). 1. Nature Sustainability, 1(1), 44–50. https://doi.org/10.1038/s41893-017-0004-x

AC: Noted and incorporated into disucssoin (Line 314-316). In their Fig. 3, Tong et al. mapped the convervation efforts in their study area most of which show low-moderate levels. They also show increasing trends of LAI in the region where croplands dominate (lower right part of their study area, with low-moderate conversation level). This indirectly supports our finding that the vegetation growth in this cultivated area has been enhanced.

RC1: Lines 272-275. This point seems important but is not fully developed. Are there results in this study showing enhanced or perhaps near-normal productivity under drier than normal condition?

AC: We have rephrased this part (Line 340-343).The possible underlying mechanisms for higher GPP in dry conditions than wet conditions are also given in the follow-on test (Line 345-348).

Anonymous Referee #2:

RC2: General comments: 1. The Pearl River Basin is in relatively humid region. Beside water, other factors may also influence the vegetation growth. It is suggested to show the landcover change in the studied period and analyze the relationship between vegetation growth and temperature or egergy to identify the vegetation-water relation more clearly.

AC: Thank you for the suggestion. It is a good one and in fact we thought about this analysis, because it is realized that the controling factors of vegetation growth can be divided into two groups – the demand (including radiation, vapor pressure deficit, and temperature, etc) and the supply groups (soil moisture, groundwater, and water storage, etc).

The supply group factor was represented by precipitation and total water storage here, and the demand effect was integrated in potential evaporation and embedded in the aridity index. In this sense, we discussed both the hydroclimate and water impacts on vegetation. We made the argument more clearly at the end of Methods section (Line 173-176).

RC2: 2. Lag effect between vegetation growth and water availability are analyzed at monthly scale. In my opinion, it is necessary to show how P, TWS, NDVI and GPP for the 12 months in a year for better discussion about the lag effect.

AC: We agree that a climatological monthly mean of these variables would help much with the lag effect analysis. We also gave this calculation and analysis in Fig. 9, and results in Fig. 10 were based on the climatological means which we failed to mention in the relevant text. Please refer to Line 248-249 in the revised version.

RC2: 3. I understand when using remote sensing products, uncertainty issue is always a concern need to be addressed. However, this is not the scientific target of this paper. To keep the readers' attention to the key scientific question trying to answer, it is suggested to remove the "uncertainties in the datasets and results" section and describe how you quantify the uncertainty of remote sensing data in the Methodology section.

AC: Thanks for the suggestion. Indeed, when using remote sensing for hydrologic studies, the data uncertainty/accuracy is often concerned. Considering that the other reviewer also mentioned this, we still kept this subsection in the revised manuscript and expand it for a detailed justification. A few supplementary figures are also provided for comparisons of different remote sensing products. Relevant text in Data and methods and Discussion has been improved.

RC2: Specific comments: Line 77: Please give more information about the importance of Pearl River Basin and it's connection with research progress described in the previous paragraph.

AC: This issue is also suggested by another reviewer. A short paragraph has been added, please refer to Line 78-89 in the revised manuscript, and the Study area section in 2.1 has been edited accordingly as well.

RC2: Line 120: It is suggested to decide the assumption being made behind the lag effect analysis

AC: We have changed the sentence '*Furthermore, a lag effect analysis …*' to '*Furthermore, to investigate the causal role of vegetation growth to water availability changes (or vice versa), we carried out lag effect analysis between vegetation parameters and hydroclimate variables. That is, we assume that vegetation growth is constrained by water resources if dynamics of NDVI/GPP falls behind dynamics of P/TWSA.*' (Line 160-163)

RC2: Line 195: The basin is in subtropical region. So please confirm whether October to March is non-growing seasons.

AC: Growing season months have been given at its first appearance (Line 241 & 246). Because it can vary from year to year for each type of vegetation cover, we use the conventional definition in this study, i.e. from April to October. Precise quantification of growing season length can be done with vegetation index time series but won't be necessary for this study.

RC2: Line 252-253: A landcover change analysis for the study period may make the explanation here more persuasive.

AC: Please refer to the response to General comment point 1, and response to the 4th comment by Prof. Zhang. In addition, we think the possible changes in planting structure would also alter the trend of greenness and productivity in these agricultural areas (added discussion in Line 345-348).

RC2: Line 254: I'm a little bit confused about "water storage increase in this hotspot region has resulted in the intensification of agricultural activities". More explanation is needed.

AC: We have rephrased this sentence as '*The changes of TWS, NDVI and GPP jointly imply that the water storage increase in this hotspot region, which was likely induced by increased precipitation, coincides with the intensification of agricultural activities and boosted the food production since the early 2000s.*.' A study by Tong et al., (2018) was used to partly support our finding here.

RC2: Figure 9: It is hard to read as many elements are overlapped together. Please find a clearer way to describe the information contained in this figure.

AC: We have separated Fig. 9a in 2 subplots, and adjusted the colors and transparency of the bands to show them as clearly as possible. Please refer to the revised figure.

Assessing the large-scale plant-water relations using remote sensing products in the humid subtropical Pearl River Basin in south China

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Abstract. Vegetation interact closely with water resources. Conventional field studies of plant-water relations ~~at the field scale~~ are fundamental for understanding the mechanisms of how plants alter and adapt to environmental changes, while large-scale studies can be more practical for regional land use and water management towards mitigating climate change impacts. In this study, we investigated the changes in total water storage (TWS), aridity index (AI) and vegetation greenness, productivity and their interactions in the Pearl River Basin since 2002. Results show an overall increase of TWS especially in the middle reaches where vegetation greenness and productivity also increased. This region dominated by croplands was identified as the hotspot for changes and interactions between water and vegetation in the basin. Vegetation was more strongly affected by TWS than precipitation (P) at both the annual and monthly scales. Further examination showed that the influence of TWS on vegetation in dry years was stronger than wet years, while the impact of P was stronger in wet years than dry years; moreover, vegetation greenness responded faster and productivity slower to atmospheric dryness changes in dry years than wet years. The lag effects resulted in nonlinearity between water and vegetation. This study implies that vegetation in the basin uses rainwater prior to water storage until ~~it~~ the soil gets dry, and the degree of water restriction on vegetation was higher than that of water consumption by vegetation even in this rain-abundant region.

1 Introduction

Vegetation covers 70% of the land surface, playing a vital role in water, carbon and energy exchanges between land and atmosphere (Yang et al., 2016). As climate change has been more and more evident since the industrial age (Marvel et al., 2019; Sippel et al., 2020) ~~which~~ resultings in numerous ecohydrological problems such as droughts, flooding, tree mortality, etc., managing land use especially through vegetation ~~cover~~manipulations has been considerably practiced in many catchment planning projects (Adhami et al., 2019; Stewardson et al., 2017). The theoretical basis for vegetation-involved catchment management is the plant-water relations across multiple scales, for example, ~~that~~ vegetation can intercept precipitation by the canopy which helps with the flood control (Soulsby et al., 2017; Wheater and Evans, 2009); they uptake soil water or groundwater and transpire it through leaves to increase moisture in the air; and the plant roots create macropores for water flow paths in soils to aid rapid recharge to soil water stores (Ghestem et al., 2011). In addition, vegetation assimilates carbon dioxide (CO_2) through photosynthesis to ~~accumulate biomass production~~produce food and energy materials and reduce greenhouse gas concentration (Notaro et al., 2007; Yosef et al., 2018). In turn, atmospheric and hydrologic conditions can affect vegetation growth by altering ~~vegetation~~ the physiological characteristics such as the openness of stomatal aperture (Reyer et al., 2013; Sala et al., 2010). Therefore, investigation of plant-water relations is of great importance in maintaining terrestrial hydrological regimes and mediating carbon cycle and energy balance in the Earth systems.

Conventional studies of plant-water relations are often carried out at the leaf and canopy level based on extensive field measurements. There are a rich pool of literatures that examine the plant responses ~~such as stomatal opening/closure~~ to stress from both atmospheric conditions and water supply (Martin-StPaul et al., 2017; Whitehead, 1998). It may be true that all ecosystems are to some degree controlled by water, but the mechanisms vary greatly (Asbjornsen et al., 2011), ~~F~~for instance, plant water use responded sensitively to rainfall pulses and amounts in dry semi-arid areas (Huang and Zhang, 2015; Plaut et al., 2013), whilst the light exposure (i.e. radiation~~energy~~) between frequent low-intensity rainfall events seemed more important to stimulate transpiration than rainfall amount~~itself~~ in the humid low-energy boreal ~~regions~~ forest (Wang et al., 2017). It is well recognized that plant-water interactions will affect soil moisture dynamics, and the ~~S~~soil water especially the root-zone moisture in turn plays a key role in regulating plant growth. The relationship is commonly characterized as linear increase of plant water use with increasing moisture within a certain range, above which plant water use maintains its potential rate and will be limited mainly by energy (Novák et al., 2005). ~~Noticeably, some studies observed a parabolic relationship between plant water use and soil moisture (Zhao and Liu, 2010) or~~, ~~groundwater level (Liu et al., 2014a).~~

The ~~site-specific (in terms of species, soil and climate)~~field studies are fundamental for deep understanding of the mechanisms of how plants alter and adapt to environmental changes (Massmann et al., 2018; Petr et al., 2015; Sussmilch and McAdam, 2017). However, it is difficult to draw universal conclusions about plant-water relations extrapolative to a large landscape comprised of multiple vegetation types and with different structures from site-specific analysis (Aranda et al., 2012; Wang et al., 2008). This phenomenon is depicted as the longstanding "scale issue" in ecohydrology (Anderson et al., 2003; Jarvis and Mcnaughton, 1986)~~.~~, which~~This~~ would weaken the applicability of observation-based research outcomes ~~on~~ during the implementation of vegetation-related ecological projects at a large scale ~~such as the *Grain for Green* and Three-North Shelterbelt Project in China to assess the long-term impacts and feedback between climate, vegetation and hydrology~~ (Liang et al., 2015). Practically, ~~A~~assessing and mitigating climate change impacts ~~such as floods and droughts~~ require effective integrated efforts at a catchment or regional scale (Fowler et al., 2019; Ma et al., 2015), therefore~~. From this perspective~~, it is necessary to investigate the plant-water relations at a larger scale beyond the field sites. From this perspective,

~~R~~remote sensing (RS) products can be very useful because the~~provide~~ abundant information ~~on~~ of land surface they contain ~~hydrology and vegetation characteristics and~~ can be beneficial in overlooking the plant-water relations from a large area and over a long period. Over the past several decades, various RS data have been applied in many fields such as water budget assessment and hydrological components estimation (Pham-Duc et al., 2019; Wang et al., 2014a), vegetation phenological variation~~y~~ and the climate change impacts (Güsewell et al., 2017; Hwang et al., 2018), ecosystem services and its linkages with climate and land use (Xiao et al., 2019), etc. The advantage of RS analysis in terms of the spatial and temporal coverage~~is that it can identify the interplay between water and vegetation over a long period and under a wide spatial coverage, and it~~ is ~~promising~~ prominent in assisting the land and water management by pinpointing the ~~hotspots~~ areas ~~for~~ where the vegetation and hydroclimate~~se~~ changes and interactions are more sensitive.

Among the studies of plant-water relations lies ~~A~~an interesting and meaningful argument~~ exists in the studies of plant-water relations~~. On the one hand, vegetation need water to survive and thus are directly influenced by water availability. For instance, the most severe eco~~logica~~system~~l~~ degradation being faced by many inland river basins is closely related to reduced water availability ~~;~~ (Yu and Wang, 2012). ~~o~~On the other hand, vegetation are effective conduits to return water from soils to the atmosphere through transpiration and interception loss, and thus can cause big water security concerns ~~if the water carrying capacity for vegetation is exceeded~~ (Xia and Shao, 2008). ~~The most severe ecological degradation being faced by many inland river basins is closely related to water availability (Yu and Wang, 2012). Meanwhile,~~It is found that in most cases an increase in forest cover will reduce water yield and soil water storage (Brown et al., 2005; Schwärzel et al., 2020) because of an increase in evapotranspiration, though the magnitudes are subject to scale, species and catchment size (Blaschke et al., 2008; Wang et al., 2008). Numerous studies prove that many dryland ecosystems are sourcing soil water recharged by precipitation or groundwater, therefore, plant ~~water use~~growth depends ~~varies~~ largely on~~with~~ rainfall pulses or groundwater level ~~in such ecosystems especially in the drylands~~ (Eamus and Froend, 2006; Xu et al., 2016; Yang et al., 2014). ~~It is worth mentioning that~~While majority of such studies were carried out in semi-arid regions because of the urgent need to find an equilibrium threshold between ecological restoration and available water resources in these water-limited areas,~~.~~ ~~However, in the humid or semi-humid areas with abundant rainfall,~~ it is still largely unclear whether the restriction of water resources or available energy on vegetation growth ~~or the consumption of water by vegetation~~ prevails in the humid or semi-humid areas with both abundant rainfall and radiation~~in the long term, because~~. T~~t~~he mechanisms of hydroclimate controls on vegetation can be different between arid and humid environments (Asbjornsen et al., 2011; Sohoulande Djebou et al., 2015).

In this study, we investigate the plant-water relationships in the Pearl River basin (PRB), the largest river basin in subtropical humid South China, which supports ~120 million populations. Water is one of the most important strategic resources in the basin, especially in one of its sub-basins - the East River basin. The East River basin provides water for the densely populated and highly economically developed delta region including Shenzhen and Hong Kong, and the water exploitation rate has nearly reached 38%, which increases the difficulty in water allocation and management among different administrative regions and water use sectors. Vegetation of both natural and cultivated covers vast areas of the Pearl River basin (>92%). With around half of the total annual precipitation leaving the basin as evapotranspiration (Gao, 2010), consumption of water by plants ~~through transpiration~~ is non-negligible and may pose threats to other water cycle components like streamflow which is the major water resource in most of the basin.

Despite previous studies examining the changes in ~~hydrologic compartments, climate change and~~ vegetation greenness and investigating the roles of climate and droughts (represented primarily by temperature and precipitation) in the PRB and its sub-basins (Lin et al., 2017; Niu et al., 2018; Wu et al., 2019; Zhang et al., 2013), there are few ~~insightful~~ studies quantifying how ~~hydroclimate and~~ vegetation ~~greenness and~~ productivity alongside greenness interact with water resources ~~at different time scales~~from the -short to long terms ~~and~~ under contrast atmospheric dryness conditions ~~in the subtropical Pearl River Basin in China over the recent 2 decades~~. Such investigation ~~Results of this study~~ can be informative for the basin-wide land and water use planning under a rapid changing environment. Thus, ~~this study is the first attempt to reveal the plant-water relations at a large spatial scale in thebasin. Specifically,~~ the objectives of this study include (1) characterizing the spatiotemporal patterns of hydroclimate and vegetation changes in the last ~~13 years~~decade or so,~~,~~ ~~and~~ identifying the hotspots for these changes and the possible driving forces; and (2) quantifying the plant-water relations at different temporal scales and under ~~different~~ contrasting dryness conditions to determine whether the restrictions of water on plant growth, or the opposite, prevail in this humid basin~~; and (3) examining the interactive role of water availability and vegetation growth~~. ~~Results of this study can be informative for the basin-wide land and water use planning under a changing environment.~~

2 Data and Methods

2.1 Study area

The Pearl River (in the range of 102–116°E, 21–27°N) ranks the second largest in China in terms of streamflow with a drainage area of ~450,000 km^2 (Fig. 1)~~, supporting the socioeconomic development of one of the most prosperous bay areas of China~~. The climate of the Pearl River Basin (PRB) is characterized as subtropical, mainly influenced by the eastern Asian monsoon and typhoons. The long-term mean annual temperature across the basin is 14–22℃, and mean annual precipitation is 1200–2200 mm (Chen et al., 2010), decreasing from southeast to northwest and primarily falls as rain and concentrates in April-September. The elevation is ~~as high as~~ ~2900 m in the west upland and decreases dramatically to the delta in the southeast, creating a maximum gradient of ~3000 m.

The dominant vegetation is ~~forest of~~ evergreen forest~~species~~ (~65.3%), followed by cropland (~18.1%) distributed mainly in the middle of the basin along a northeast-southwest transect, where happens to be in the transitional areas of high-to-low elevations in Guangxi province. Grassland (~9.3%) is the third largest land cover type mostly located in the west upland. Due to the downstream location, flat terrain, and rapid population growth and economic development, the Pearl River Delta tends to be more and more vulnerable under natural hazards such as flood and storm surge in wet seasons and saltwater intrusion in dry seasons (Liu et al., 2019). In the recent 2 decades, droughts were found to occur frequently in the basin and affected water allocation to different municipal areas and industries (Deng et al., 2018; Xu et al., 2019).

2.2 Data sources~~,~~ and pre-processing ~~and analysis~~

To assess the plant-water relations at a large spatial scale, we obtained hydroclimate and vegetation data from different sources (Table 1). Total water storage (TWS) change is inferred by the mass change detected by GRACE satellites (Tapley et al., 2004). GRACE data can be accessed from the Jet Propulsion Laboratory (JPL), the Center for Space Research (CSR), and the German Research Centre for Geosciences. Previous studies have shown that the ensemble mean of different products is effective in reducing the noise in the gravity field solutions (Long et al., 2017; Sakumura et al., 2014). Therefore, we calculated the mean values of monthly TWS anomaly (TWSA) data from the JPL and CSR that are based on the ‘mascons’ solution (release 6) at a resolution of 0.5° and monthly. Monthly TWSA is the result of subtracting the average TWS over the period of 01/2004-12/2009 from each monthly TWS value. ~~In addition,~~ GRACE$_{JPL}$ data uncertainties are given by these processing centres as the measurement and leakage errors ~~for GRACE$_{JPL}$~~ (Swenson and Wahr, 2006; Wiese et al., 2016). In this study, when showing the basin-average monthly/annual TWSA dynamics, we used the standard deviation to define the uncertainty range for the entire basin.

Precipitation (P) ~~and potential evapotranspiration (ETp)~~ data were obtained from Global Land Data Assimilation System (GLDAS) ~~;~~ (Rodell et al., 2004) and the national standard meteorological stations distributed across the basin from the China Meteorological Administration (CMA). Comparison of P from GLDAS and stations is given in the supplementary document Fig. S1, which shows that ~~aridity index (AI) was then calculated as the ratio of ETp to P to represent the dryness condition. GLDAS uses meteorological forcing data merged from multiple sources including ground and satellite observations, and GLDAS precipitation proves to be highly consistent with observations in China . Here we also compared the GLDAS P with the measured P in the pixels where stations are available (Fig. 11). O~~overall, P from GLDAS agreed well with observations with R^2 ranging from 0.69 to 0.89 ~~(±0.05)~~ spatially, while on average the monthly P from GLDAS slightly underestimated observations ~~by ~10%~~ over all valid pixels (R^2=0.98). The comparison provides some confidence in applying the gridded GLDAS ~~products~~P for long-term and spatial hydrological trend analysis in this basin~~, though discrepancies exist in the absolute values~~. Potential evapotranspiration (ETp) was obtained from the GLDAS~~,~~ and MODIS ~~and PML~~, and comparisons among them are given in Fig. S2-3, which show that ~~xxx~~both products show ETp has been increasing over the 13 years, although GLDAS gave generally higher ETp than MODIS. GLDAS shows that ETp increase was largest over the croplands in the middle-south of the basin. Spatially, the correlation coefficient between these two ETp datasets ranges from 0.26 to 0.87 at the monthly scale and -0.11 to 0.76 at the annual scale. Temporally, the average ETp from GLDAS is 1579±102~~3.7~~ and 1504±~~11.5~~4 mm yr^{-1}, and the coefficient of determination (R^2) between ETp from the two sources is 0.58 and 0.51 at the monthly and annual scale, respectively.

~~Total water storage (TWS) change is inferred by the mass change detected by GRACE satellites . GRACE data can be accessed from the Jet Propulsion Laboratory (JPL), the Center for Space Research (CSR), and the German Research Centre for Geosciences. Previous studies have shown that the ensemble mean of different products is effective in reducing the noise in the gravity field solutions . Here we used total water storage anomaly (TWSA) data from the JPL and CSR with ‘mascons’~~

~~solution (release 6) at a resolution of 0.5° and monthly. Cubic spline interpolation was applied to estimate the missing monthly data for the GRACE$_{JPL}$ and GRACE$_{CSR}$ products during 04/2002–03/2015 that cover 13 hydrological years.~~To reduce the effect of errors embedded in each individual product, we calculated the average ETp from the ~~three~~two sources for later analysis. Aridity index (AI) was then calculated as the ratio of ETp to P to represent the atmospheric dryness condition.

Vegetation data ~~in this study~~ include Normalized Difference Vegetation Index (NDVI) and Gross Primary Production (GPP) representing surface greenness and productivity, respectively. NDVI was obtained from the GIMMS project at a 15-day and 1/12° resolution ~~during 04/2002–03/2015~~ and resampled to 0.5° using the nearest neighbour method, and then averaged to monthly ~~to match the spatiotemporal resolution of GRACE and GLDAS data~~. GIMMS NDVI is among the most popular vegetation index datasets for analysis of vegetation phenology and its relationship with hydroclimate change (Cong et al., 2013; Jeong et al., 2011), especially for studies in a relatively large river basin as it covers a moderately long time period (since 1980s). Monthly GPP was obtained from the Numerical Terradynamic Simulation Group in the University of Montana (Running et al., 2004) and rescaled to 0.5°. We also obtained GPP data from VPM (Zhang et al., 2017b) and PML-v2 (Zhang et al., 2019). Comparisons of these GPP datasets are given in Fig. S4-5, which shows that spatially the GPP values from MODIS and VPM are more comparable than~~d~~ PML which provides higher values. The annual trends inferred by the three products vary across the basin, mostly within the range of -25 to 25 gCm^{2} yr^{-1}. Correlation coefficients between each two GPP datasets are high at both the monthly and annual scales, especially over the areas where croplands predominate~~.~~ However, without extensive gridded ground observations in the basin to validate these datasets, it is hard to conclude which one is most accurate. With the assumption that the ensemble mean values from multiple datasets can effectively reduce data uncertainty lying in an individual dataset, we used the mean GPP from the three sources for further analysis.

Information of data sources, resolution and time span for all variables related to this study is listed in Table 1. To compare with GRACE data, anomalies of P, AI, NDVI, and GPP data were calculated by subtracting the means over the same baseline period of GRACE data (i.e. 01/2004–12/2009). All variables were obtained from 04/2002 to 03/2015 covering 13 hydrological years. Cubic spline interpolation was applied to fill the missing monthly data for the GRACE, MOD16/17 and PML.

2.3 Data analysis

To investigate the changes in hydroclimate and vegetation, we carried out trend analysis using the Mann-Kendall (MK) test method both in space and in time. The MK test does not require normality of time series and is less sensitive to outliers and missing values (Pal and Al-Tabbaa, 2009). This non-parametric test method has been used in many studies to detect changing hydrological regimes (Déry and Wood, 2005; Zhang et al., 2009). Interplay between hydroclimate and vegetation was quantified by linear regression; the Pearson correlation coefficient (r) and coefficient of determination (R^2) were taken as a measure for assessment of the linkages between different variables. Data series were detrended by removing the linear trends before analysing their relationships at both the monthly and annual scales. Furthermore, to investigate the causal role of vegetation growth to water availability changes (or vice versa), we carried out lag effect analysis between vegetation parameters and hydroclimate variables~~a lag effect analysis was carried out to determine the temporal dependency between variables where the linear relationship was not obvious~~. That is, we assume that vegetation growth is constrained by water resources if dynamics of NDVI/GPP falls behind dynamics of P/TWSA.

Since the interactions between hydroclimate and vegetation can be different under dry and wet conditions, we ~~hereby~~ selected dry and wet years according to the annual ~~anomalies~~ dynamics of TWS, NDVI, GPP and AI under the criteria that dry conditions correspond to low negative anomaly values of TWS, ~~and~~ NDVI and GPP in addition to high positive anomaly of AI. The~~n the~~ relationships between hydroclimate dynamics and vegetation greenness and productivity were specifically analysed in these dry and wet years. Uncertainties of the data used were estimated by the standard error of each variable at the monthly and annual scales. It is worth mentioning that vegetation growth is usually controlled by two groups of factors, i.e. the demand (e.g., radiation, vapor pressure deficit, and temperature, etc) and the supply (e.g., soil moisture, groundwater, and water storage, etc). The supply control was represented by P and TWS here, and the demand effect was integrated in ETp and embedded in the aridity index. In this sense, we have the impacts of both groups accounted for on vegetation growth.

3 Results

3.1 Changes in water storage and dryness

Comparison of the GRACE data from JPL and CSR shows that mean annual TWSA from $GRACE_{JPL}$ was overall greater than that from $GRACE_{CSR}$ (Fig. 2a-b). Both products showed clear zonal characteristics similar to the average of the two (Fig. 2c) that TWSA was generally higher in the middle-to-east areas than the rest of the basin especially the west upland, which infers a generally wetting condition in comparison to the baseline period. The trends of annual TWSA (Fig. 2d) showed that over the 13 hydrological years the TWS in most of the basin has increased at a rate below 10 mm yr^{-1} with 46% of the total area in the range of 5.0–10.0 mm yr^{-1}. Areas with low changing rate were mainly located in the west upland where the predominant land cover is grassland with underlying karst limestones. ~~Like the distribution of TWSA, water storage increase rate was also higher in the middle-to-east areas, where overlap partly with croplands, than the rest of the basin.~~

Temporally, the basin has been getting wetter in general from 2002 (Fig. 2e). The TWSA has increased over the 13 years (not statistically significant) by 6.8±2.6 mm yr^{-1} inferred by $GARCE_{JPL}$ and 4.6±1.0 mm yr^{-1} by $GRACE_{CSR}$, with an average of 5.9±1.4 mm yr^{-1}. In the following sections, only the mean TWSA from $GRACE_{JPL}$ and $GRACE_{CSR}$ was used for analysis. Noticeably, there were three shifts in the drying and wetting tendencies over the study period, i.e. the shift from drying between 2002 and 2005 to wetting between 2005 and 2008, followed by the shift back to drying between 2008 and 2011, and finally the shift to wetting after 2011.

Fig. 3 shows the aridity index (AI) characterizing the spatial and temporal patterns of dryness. Majority of the basin has a semi-humid climate (AI=1.0~1.5); the west upland was clearly drier than the rest of the basin which is associated with precipitation patterns ~~in this basin~~. Although dryness condition has not changed significantly over the 13 years with an overall positive trend ~~in space~~spatially (0.002±0.009) and ~~time~~ temporally (0.005±0.025), it has some interesting characteristics such as the wetting tendencies primarily located in the ~~southern~~ cropland areas, and the alternate periodical wetting and drying episodes temporally also existed like TWSA. Areas with low TWS change rates generally coincided with drying climate represented by aridity index.

3.2 Changes in vegetation greenness and productivity

Spatial NDVI distributions (Fig. 4) were highly related to vegetation cover types that the high NDVI values coincided with forest covers and low values corresponded to impervious surfaces, grasslands and croplands. It clearly reflects the impacts of urbanization on surface greenness particularly near the basin outlets in the southeast. Over the 13 years NDVI has not shown significant changes across the basin, since the majority (~70.3%) had a MK test p>0.05 at the pixel scale. The areas with significant changes were concentrated in the central south of the basin where croplands are predominant~~. This infers~~, ~~show~~indicating a~~n~~ possible intensification of crop farming activities over these areas.

Temporally, NDVI has an overall insignificant increase trend over the 13 years at an annual rate of 0.004±0.003 (p=0.56) with interannual fluctuations. However, i~~I~~t is noticeable that the periodical shifts in the NDVI trends were almost identical to TWSA in Fig. 2e. This reflects a tight bound between the vegetation greenness and water availability in this rain-abundant region at the annual scale. Interestingly, in 2004 when water storage continued to decrease following the previous years, NDVI did not show a continuity of decreasing but increased instead, ~~implying a vegetation resilience and recovery after previous dry period. The recovery~~ coincided with a slight decrease in aridity index~~, hence, vegetation did not respond solely to water availability but also to atmospheric demand~~.

In addition to NDVI, vegetation parameter GPP was also analysed for the basin (Fig. 5). It is not surprising to observe that GPP was highly responsive to NDVI such that areas with low NDVI also had low GPP (e.g., the central agricultural region and upland grassland). GPP anomaly also showed positive high values in the central south areas dominated by croplands coincident with NDVI anomaly, indicating an increased agricultural production induced by intensified agricultural activities in this region. It should be noted that ~~most of~~ the trends were ~~not~~ statistically significant only in 33.6%~~a limited number~~ of all pixels, many of which are located in the cropland areas. Over the entire basin, annual GPP showed almost the same periodical decreasing and increasing trends as NDVI and TWSA, except that the third turning point occurred in 2010 rather than 2011. Linear regression gave a coefficient of determination R^2=0.59 (p=0.002) between annual TWSA and NDVI, higher than that between TWSA and GPP (R^2=0.23, p=0.099), which may imply a more direct and stronger ~~impact~~ dependence of vegetation greenness than productivity on water ~~stress~~ storage at an annual scale.

3.3 Interactions between hydroclimate and vegetation

Combining Fig. 2-5, we found that climate condition, water storage and vegetation dynamics are tightly interlinked. Coefficient of determination between anomalies of these variables (Fig. 6) show that variation of annual NDVI can be explained by TWS by 58.6% (p=0.002), followed by P (36.5%, p=0.029) and AI (10.8%, p=0.272). Influence of these three variables on GPP followed the same order (R^2=0.23, 0.06, 0.02) but not statistically significant (p>0.05). In addition, GPP was positively associated with NDVI (R^2=0.35, p=0.033), and P and TWS were negatively correlated with dryness (p<0.05).

Spatially, precipitation, water storage and dryness affected vegetation in a similar way compared to temporal characteristics, i.e. the influence of TWS was relatively stronger than P and AI. The hotspots of the interactions were found in the middle-south areas, and dryness more negatively affected greenness than productivity in these areas (Fig. 7). ~~These analyses indicate that a~~Atmospheric stress and water stress imposed more direct and stronger impact on vegetation greenness than productivity on a yearly basis, and water constraint on vegetation was stronger than that of dryness.

At the monthly scale, however, the linear responses of GPP to P and TWS were stronger than the linear responses of NDVI to P and TWS (Fig. 8a-b). The response of both NDVI and GPP to P was more nonlinear than to TWS, and the sensitivity of NDVI and GPP to TWS was stronger than to P indicated by the regression slopes, implying a stronger link between water storage and vegetation growth. Meanwhile, increase in dryness resulted in nonlinear decreases in NDVI and GPP (Fig. 8c). The relationships show that although precipitation is the main water input to the terrestrial hydrological cycle, it is how much water is stored in the soils that determines vegetation greenness and biomass production~~ at a shorter time scale than annual~~.

Nonlinear plant-water relationships can be explained by the lag effect that monthly changes of NDVI and GPP fell behind the changes of P and TWS to varying degrees (Fig. 9). In other words, the decline of water resources results in reduction in vegetation greenness and productivity, not the opposite. This means that the~~ water restriction~~impacts of water availability on vegetation growth outweighed the ~~water consumption by~~impacts of vegetation growth on water resources depletion. Vegetation response to hydroclimate changes is expected to differ in dry and wet years. Here, we assumed that the annual anomalies of TWS<0, NDVI<0 and AI>0 corresponded to dry conditions, and hence defined 2003, 2005, 2007, 2009 and 2011 as dry years and 2002, 2006, 2008, 2010, 2012-2014 as relatively wet years. There was evidence of drought occurrences in these dry years (Lin et al., 2017; Wang et al., 2014b). It can be seen that the dry and wet years were mainly differentiated by the rainfall data in summer months July and August affecting water storage and dryness. The range of long-term mean monthly NDVI and GPP was 34.0% and ~~8.4~~14.6% ~~higher~~ greater ~~on average~~ in dry years than wet years, mainly attributable to the difference in the non-growing seasons from ~~October~~ November to March (Fig. 9c-d). Both the minimum and maximum NDVI were lower in dry years than in wet years, particularly, the minimum NDVI in dry years was 81.1% lower than that in the wet years, compared to 12.6% lower for the maximum. Difference of GPP was not large~~similar~~

between~~in~~ dry and wet years, with 14.3~~9.8~~% ~~and 6.9%~~ lower and 14.9% higher in dry years for minimum and maximum values, respectively. This implies firstly that vegetation greenness is more sensitive to any changes in hydroclimate than productivity, and secondly that~~.~~ ~~Moreover,~~ GPP in growing seasons (i.e. October to April in general definition) in dry years was relatively higher than that in wet years reflecting a positive effect of water stress on biomass accumulation.

Fig. 10 gives the R^2 from linear regression between the monthly climatological means of different variables considering phase shift for lag analysis over all the years, dry and wet years, respectively. It shows NDVI varied strongest with P, TWSA and AI in the previous 3, 1 and 3 months, respectively when considering all data during 2002-2014. In comparison, a shorter lag time of GPP to P, TWSA, and AI was detected (~~2~~1, 0, 1 month, respectively). Comparison of the lag time in dry and wet years shows that the influence of P on vegetation was more prominent in wet years than in dry years, while TWS influence was greater in dry years than wet years. Moreover, NDVI responded faster to dryness change in dry years (2 months) than wet years (3 months), and GPP responded slower to dryness change in dry years (1 month) than wet years (0 month). This may indicate that drying to some degree can stimulate biomass production. In addition, GPP varied synchronously with TWS showing a high dependency on water storage despite the dryness conditions.

4 Discussion

4.1 Uncertainties in the datasets and results

Data availability is one of the greatest obstacles for large-scale and long-term ecohydrological studies. Remote sensing products are thus useful to characterize ecohydrological changes in a large sparsely monitored basin. In this study, we used remote sensing and assimilated data of water storage, vegetation status and precipitation to assess their relationships. Precipitation is one of the commonly monitored meteorological variables,

usually with relatively long time series and wide spatial coverage. We compared P data from GLDAS and meteorological stations in Fig. S1. It shows that the two datasets agree well both spatially and temporally. The spatial coefficients of determination (R^2) range from 0.7 to 0.9 in pixels where stations are available, and the temporal R^2 is 0.98 with a close-to-one regression slope. The comparison indicates that the gridded GLDAS precipitation data can be used to analyse the dynamics and relationships of hydroclimate and vegetation parameters. Potential evapotranspiration (ETp) is used to calculated aridity index, therefore, we also obtained and compared ETp in Fig. S2-3, which shows that spatially the correlation coefficient between monthly and annual ETp lies mostly in 0.6~1.0 and 0.4~1.0, showing relatively good agreement; and temporally ETp are close to each other at the monthly scale while the uncertainty enlarges at the annual scale. In lack of ground truth data, and with the assumption that ensemble means can reduce the errors in each individual product, we calculated the average ETp from the two sources for analysis.

GPP data from MODIS have been extensively used in literature to facilitate studies of vegetation in response to climate and hydrology. For example, A et al. (2017) discussed the relationship between TWS, soil moisture and GPP in response to drought in 2011 in Texas, USA, and found that vegetation dependency on TWS weakened in the shrub-dominated west and strengthened in the grassland and forest area. Liu et al. (2014b) compared five GPP datasets against observations at six sites across China and concluded that MODIS GPP was more reliable over grassland, cropland and mixed forestland than the other datasets. These land cover types happen to be the predominant ones in the Pearl River Basin, which assures some degree of confidence in GPP analysis using MODIS product in this study. Zhang et al. (2017b) and Yuan et al. (2015) also compared various GPP datasets globally and regionally, and inconsistencies existed in these comparisons that could stem from the way each algorithm parameterizing atmospheric and water stress and difference in the vegetation index data (Yuan et al., 2015). From the supplementary Fig. S~~1-S2~~4-5 for comparison of three GPP datasets, we found spatially the GPP values from MODIS and VPM are more comparable than PML which provides higher values. The annual trends inferred by the three products vary across the basin, mostly within the range of -25 to 25 gCm^2 yr^{-1}. Correlation coefficients between each two GPP datasets are high at both the monthly and annual scales. It is worth mentioning that the algorithms for MODIS, VPM and PML only account for atmospheric restrictions (including vapor pressure deficit, temperature, and radiation) but none accounts~~t~~ for soil water availability (Pei et al., 2020), in which case the GPP could be overestimated. However, without extensive gridded ground observations in the basin to validate these datasets, it is hard to conclude which one is most accurate~~GPP from MODIS is comparable to that from PML, while they both are higher than the other product. These three datasets spatiotemporally agree well with~~ ~~R^2>0.90 between each two. The comparisons show the confidence in terms of consistency in their temporal trends. Despite the dispute of data accuracy, MODIS GPP seems more frequently used due to its moderate spatiotemporal resolution and data coverage. Nonetheless, without ground truth data for validation and application in such a large catchment, these remote sensing products are promising and useful.~~

Regarding the water storage change, the distribution and magnitude in the middle and lower reaches of the basin was similar to the results in Luo et al. (2016), but the increasing trends of TWS were detected in the upland opposite to their study. This could be attributable to firstly that they used 1° GRACE data (release-5) during 2003-11/2014 and we used 0.5°data (release-6) during 04/2002-03/2015, and secondly the way the annual values were calculated: we used the hydrological year (i.e. April to March of next year) instead of the calendar year. In addition to this study and Luo et al. (2016), Zhao et al. (2011) found an overall significant increase of 9.2 mm yr^{-1} in TWS using 1° GRACE data during 02/2003-02/2009; Mo et al. (2016) detected also a significant increase of TWS by 5.5 mm yr^{-1} using 1° GRACE data during 2003-2013; Long et al. (2017) used the 0.5° GRACE data (release-6) for TWS analysis and found a significant increase trend of 6.3 mm yr^{-1} during 04/2002-03/2015. It is thus important to consider the data source, spatial resolution and temporal coverage (due to interannual variability) when detecting the TWS trends for comparison. Nonetheless, it can be concluded that TWS in the PRB has been steadily increasing from the early 2000s at a rate of ~6 mm yr^{-1}.

~~GPP data from MODIS have been extensively used in literature to facilitate studies of vegetation in response to climate and hydrology. For example, A et al. (2017) discussed the relationship between TWS, soil moisture and GPP in response to drought in 2011 in Texas, USA, and found that vegetation dependency on TWS weakened in the shrub-dominated west and~~

~~strengthened in the grassland and forest area. Liu et al. (2014b) compared five GPP datasets against observations at six sites across China and concluded that MODIS GPP was more reliable over grassland, cropland and mixed forestland than the other datasets. These land cover types happen to be the predominant ones in the Pearl River Basin, which assures some degree of confidence in GPP analysis using MODIS product in this study. Zhang et al. (2017b) and Yuan et al. (2015) also compared various GPP datasets globally and regionally, and inconsistencies existed in these comparisons that could stem from the way each algorithm parameterizing atmospheric and water stress and difference in the vegetation index data (Yuan et al., 2015). From the supplementary Fig. S1-S2 for comparison of three GPP datasets, we found GPP from MODIS is comparable to that from PML, while they both are higher than the other product. These three datasets spatiotemporally agree well with~~ ~~R^2>0.90~~ ~~between each two. The comparisons show the confidence in terms of consistency in their temporal trends. Despite the dispute of data accuracy, MODIS GPP seems more frequently used due to its moderate spatiotemporal resolution and data coverage. Nonetheless, without ground truth data for validation and application in such a large catchment, these remote sensing products are promising and useful.~~

Inspired by the studies of TWS change using GRACE satellite data with different processing algorithms (Long et al., 2017; Sakumura et al., 2014), it may be more accurate and informative by using the average values from as many available datasets for the targeted ecohydrological variables as possible, i.e. the ensemble means, than using a single dataset. This is worth further investigation which could enhance the studies in many ungauged basins for critical hydrological assessments given the increasing availability of remotely sensed and assimilated datasets.

4.2 Hotspot for hydroclimate and vegetation changes

NDVI and GPP shared the same spatial patterns and high GPP corresponded to high NDVI in the forested areas. Low values existed in the west upland with grass cover and the central south areas of croplands. Over the 13 hydrologic years NDVI and GPP ~~showed~~ have increased ~~insignificant changes~~ by 0.004 (unitless, p=0.563) and 8.57 gCm^2 yr^{-1} (p=0.038), respectively, with large interannual variabilities. Unlike the north China where vegetation cover is deeply affected and largely recovered through decades of ecological restoration projects (Chen et al., 2019; Feng et al., 2005), vegetation cover especially the forest cover which occupies most of the PRB almost remained constant from early 2000s at least in Guangdong province located in the east of the basin (Chen et al., 2015). ~~Even so, w~~We identified the areas with significant increase in NDVI and GPP in the central south region of the basin where croplands dominate. ~~Therefore, considering that the precipitation gradually decreases from southeast coastal area toward northwest outback of the basin,~~ The changes of TWS, NDVI and GPP jointly imply that the water storage increase in this hotspot region, which was likely induced by increased precipitation, ~~has resulted in~~coincides with the intensification of agricultural activities and boosted the food production since the early 2000s. Tong et al., (2018) showed that leaf area index has increased in these cropland-dominated areas where have undergone low to moderate conservation efforts through ecological engineering. Their results support our finding indirectly that the agricultural activities in this cultivated area have been enhanced. It should be mentioned that the changes in planting structure in these agricultural areas could also result in enhanced greenness and improved productivity compared to the traditional cultivated crops, but this cannot be quantified without detailed crop data throughout the years. Nonetheless, ~~I~~it is for the first time in studies to reveal such phenomenon and can be meaningful for the food-water nexus studies in this region, and indicative for a possible ~~shift~~ expansion of China's main food production from the north to the south in the context of water and energy richness in the south and shortages in the north (Kuang et al., 2015).

4.3 Causal roles of water and dryness in vegetation changes

The overall TWS increase is promising for the managers and users of water resources in the PRB, however, the strong correlation with precipitation seasonality restrained the available water in the relatively dry periods. In fact, previous studies have reported the contribution and restriction of P to TWS. For instance, Chen et al. (2017) revealed the liability of P to TWS (r=0.78) in the PRB. Mo et al. (2016) found TWS more strongly explained (60%) by annual P in river basins in south China than in north China. In this sense, storage shortage in dry periods subject to seasonal reduction of precipitation would hamper vegetation growth. Analysis in this study shows that NDVI was highly correlated with TWS and P at the annual scale (Fig. 7), consistent with previous studies in the PRB and other areas (Guan et al., 2015; Zhaos et al., 2016; Zhu et al., 2018). Whilst at the monthly scale NDVI was still strongly influenced by TWS but not so strongly by P, in comparison to the strong response of monthly GPP to both P and TWS. The weakened linear influence of P on NDVI at the monthly scale, found also by others such as Bai et al. (2019) and A et al. (2017), can be explained by the lag effect that NDVI lagged by 3 and 1 months after P and TWS, respectively. In comparison, the lag time between GPP, P and TWS was 2 and 1 month shorter than NDVI versus P and TWS (Fig. 10a). The differences in NDVI and GPP response to hydroclimate variables may lie in the way these two parameters are calculated, especially that GPP is calculated based on atmospheric variables like temperature, vapor pressure deficit and photosynthetically active radiation (Pei et al., 2020). Because of the asynchrony in the atmospheric variables and NDVI (Piao et al., 2006), the GPP and NDVI would also have some inconsistency in time. This would further indicate that it should be given more caution when choosing parameter (NDVI or GPP) to better represent~~flect~~ vegetation growing status, which is lack in literature for discussion.

In addition, comparison of the plant-water relations in dry and wet years showed a slower response of GPP to aridity index in dry years than wet years (Fig. 10b-c). Wilcoxon rank sum test shows that the areal mean NDVI and GPP in dry years are not significantly different from those in wet years (p=0.12 and 0.76) (Fig. 9c-d). In fact, GPP was higher in the growing seasons in dry years than wet years, and NDVI was lower in non-growing seasons of dry years than wet years. Together, these comparisons may imply that a certain degree of drying can stimulate biomass accumulation. This phenomenon is also revealed by other studies (Zhang and Zhang, 2019). The underlying mechanisms could be similar to the principle of regulated irrigation in agricultur~~e~~al practice to increase water use efficiency under a certain degree of water stress (Chai et al., 2016), or that the atmospheric conditions are more favourable for photosynthesis during dry years than wet years (Restrepo-Coupe et al., 2013; Zhang and Zhang, 2019), given that the soil water or groundwater storage is not depleted severely in these dry years. This dryness effect on ecosystem productivity cannot be detected in the annual scale assessment (Brookshire and Weaver, 2015; Yao et al., 2020). These results indicate firstly that pre-growing season hydroclimate conditions play a key role in the follow-on vegetation growth and production (Wang et al., 2019), and secondly that water limits vegetation even in this subtropical radiation- and rain-abundant region instead of water shortage resulted from vegetation establishment. It cannot be detected at the time scales investigated in this study that vegetation consumes excessive water through transpiration that results in obvious reduction in water storage. However, the causal role of vegetation in water decline has been reported at mostly a shorter time scale like daily and sub-daily, such as the studies in a poplar stand in Northwest China by Shen et al., (2015) and a pine-dominated catchment in Sierra Nevada, USA by Kirchner et al., (2020), who demonstrated that sap flow by trees led to decline in groundwater level.

~~Anomalies of TWS, aridity index and NDVI together well defined the occurrences of drought in the basin that are identical to other studies using P, TWS alone or other drought indices (Wang et al., 2014b; Zhang et al., 2018).~~ The drying episodes confined the vegetation greenness and production ~~(Lin et al., 2017)~~. Liu et al. (2014a) reported that China's national total annual net ecosystem productivity exhibited declines during 2000-2011, mainly due to the reduction in GPP caused by extensive drought. Although drought is generally associated with declines in vegetation greenness and productivity due to water and heat stresses (Eamus et al., 2013), the magnitude of vegetation reduction, determined by ecosystem sensitivity to drought, can vary dramatically across plant communities and thus show different spatial patterns relative to different vegetation types. While Zhang et al. (2017a) detected insensitivity of vegetation to droughts in humid south China including the lower reach of PRB, this study observed that NDVI experienced a recovery in 2004 after drought in the previous year, which may be a result of irrigation during drought in the agricultural regions since forests are more resilient to droughts (DeSoto et al., 2020; Fang and Zhang, 2019). Future climate projections predict increases in temperature and insignificant changes in precipitation in the basin which would trigger more heatwave induced flash droughts (Li et al., 2020). This would likely enhance the atmospheric controls on vegetation development. To mitigate the impacts on both water resources and ecosystems, proper plans should be made such as conversion of the low resilient ecosystems to forests (Fang and Zhang, 2019) and improvement of biodiversity in ecosystems (Isbell et al., 2015; Oliver et al., 2015), in addition to engineering regulations like reservoir operations (Lin et al., 2017).

5 Conclusions

Plant-water relations over the Pearl River Basin were examined using remote sensing products during the hydrological years of 2002-2014. Results show that water storage has increased across the entire basin at an average rate of 5.9 mm yr^{-1}. Vegetation greenness and productivity has also shown some changes with significant increases concentrated in the cultivated lands. Spatial characterization reveals that the central south areas of the basin dominated by croplands are the hotspots for the changes of and interactions between hydroclimate and vegetation. This implies an increase in food production induced by intensification of agricultural activities in these areas. Lag effect analysis at the monthly scale reflects that even in this rain-abundant subtropical basin the water restriction on vegetation precedes the water consumption by vegetation. Furthermore, comparison of the plant-water relations in dry and wet years showed a stronger influence of precipitation and a weaker influence of water storage on vegetation in wet years than dry years. A slower response of vegetation productivity to aridity index in dry years than wet years was identified which may indicate a stimulating role of a certain degree of drying~~ness~~ on vegetation production. Therefore, essentially the vegetation growth in this subtropical humid region is more strongly controlled by atmospheric demand factors than water supply factors. This study reveals the changes and interplay between plant and water using readily available remote sensing and assimilated data~~,~~ and has implications for proper measures regarding land use alterations to mitigating frequent drought impacts on water resources and ecosystems under a warming climate.

Data availability

The original data in the study are available from the links given in Table 1.

Author contribution

Wang: Conceptualization, Methodology, Writing – original draft, review& editing; Duan: Methodology, Writing – review & editing; Liu & Chen: Writing – review & editing, Validation.

Competing interests

The authors declare that they have no conflict of interest.

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Table 1. Information of data used in this study

	Product	**Resolution**	**Time span**	**Data link**
P	GLDAS-Noah (v2.1)	0.25°×0.25°, Monthly	04/2002–03/2015	https://disc.gsfc.nasa.gov
	CMA	Station-based, monthly	04/2002–03/2015	http://data.cma.cn/data
ETp	GLDAS-Noah (v2.1)	0.25°×0.25°, Monthly	04/2002–03/2015	https://disc.gsfc.nasa.gov
	MOD16A2	0.05°×0.05°, Monthly	04/2002–12/2014	http://files.ntsg.umt.edu/data/NTSG_Products/MOD16/
TWSA	GRACE (RL06)	0.5°×0.5°, Monthly	04/2002–03/2015	http://grace.jpl.nasa.gov; www2.csr.utexas.edu/grace/RL06_mascons.html
NDVI	GIMMS3g (v1)	0.083°×0.083°, 15–day	04/2002–03/2015	https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1
GPP	MOD17A2	0.05°×0.05°, Monthly	04/2002–12/2014	www.ntsg.umt.edu/project/modis/mod17.php
	VPM	0.05°, monthly	04/2002–03/2015	https://figshare.com/articles/Monthly_GPP_at_0_05_degree/5048113
	PML-v2	0.05°, 8-day	07/2002–03/2015	https://github.com/kongdd/PML

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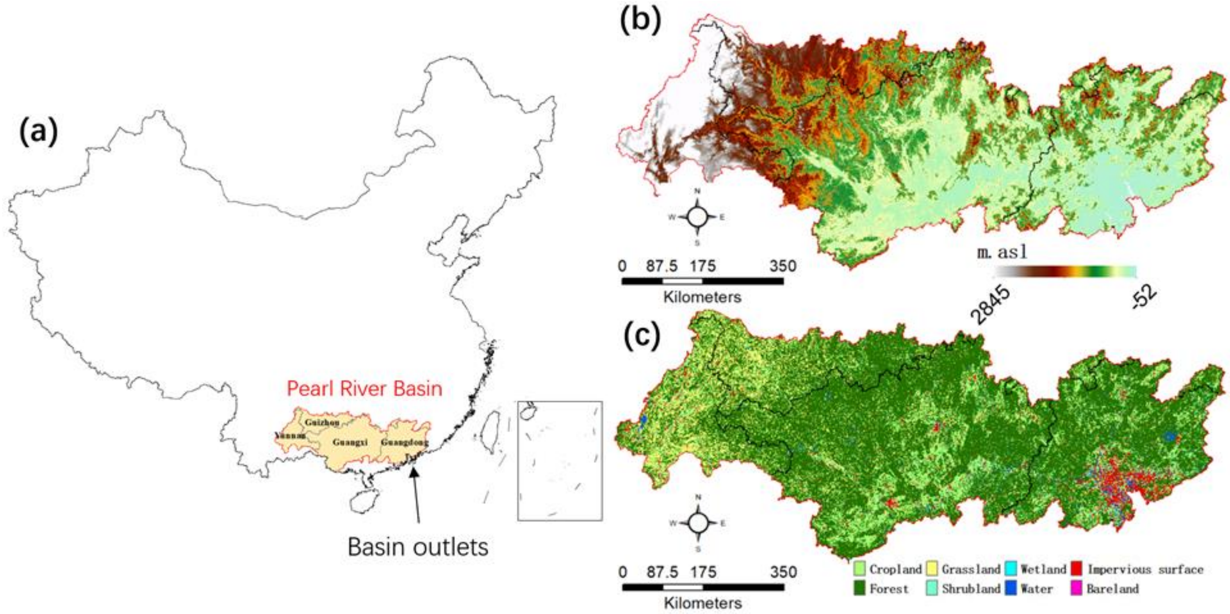

Figure 1. (a) The Pearl River Basin and the related provinces on the map of the China, (b) Digital elevation map (m.a.s.l, 1000 m resolution), and (c) Land cover types (30 m resolution).

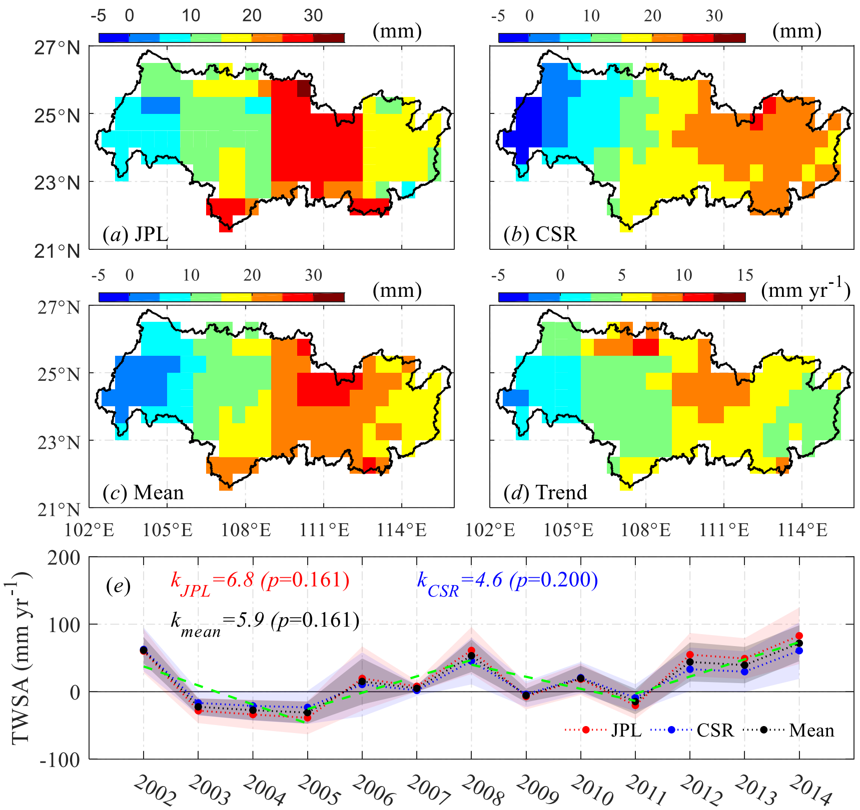

Figure 2. Spatial distribution of TWSA in the basin inferred by (a) $GRACE_{JPL}$, (b) $GRACE_{CSR}$, (c) the mean of $GRACE_{JPL}$ and $GRACE_{CSR}$, (d) the linear trends of the mean annual TWSA, and (e) mean annual TWSA over the entire basin. Shaded areas in (e) show the standard error of each series. Dashed green lines indicate statistically insignificant trends (R^2=0.68, 0.82, 0.58 and 0.83, respectively).

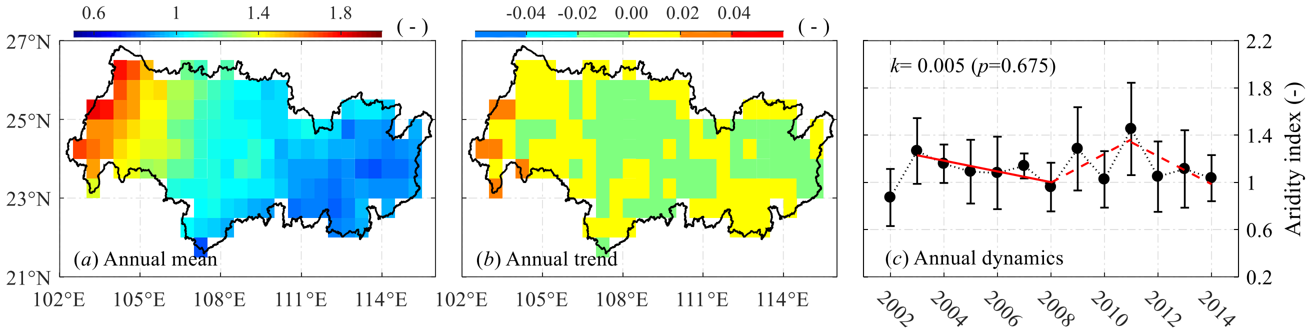

Figure 3. (a) Spatial distribution of the mean annual aridity index across the basin during hydrological years 2002-2014, (b) annual trend of aridity index, and (c) mean annual aridity index over the basin. Red lines show the periodical trends. Dashed red line indicates statistically insignificant trend. The coefficient of determination is 0.71, 0.47 and 0.61, respectively.

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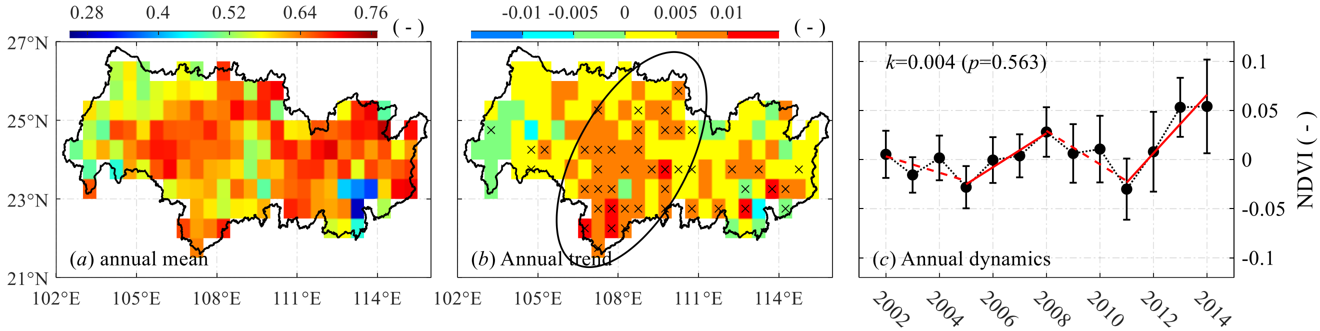
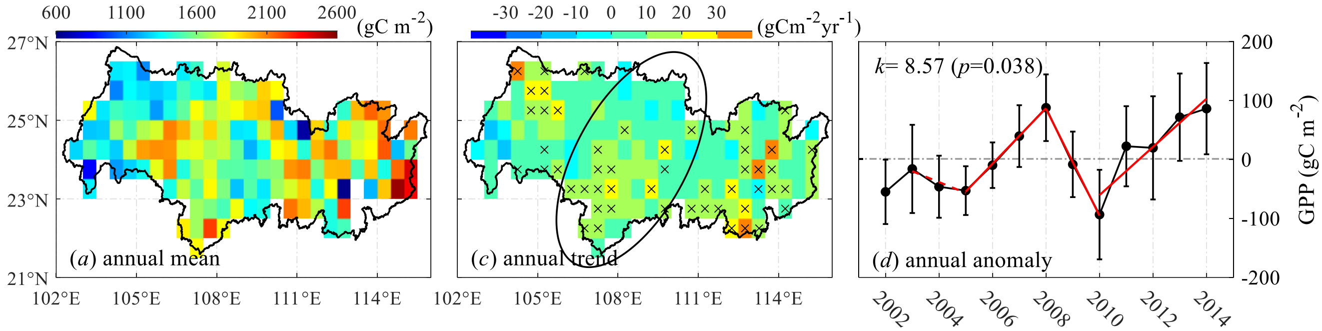


Figure 4. Spatial distribution of (a) mean annual NDVI, (b) linear trend of annual NDVI with crosses indicating significant trends; and (c) spatially averaged annual NDVI anomaly, during 2002-2014. Red lines show the annual trends in different periods. Dashed red lines show statistically insignificant trends (p>0.05). Coefficient of determination is 0.47, 0.94, 0.81 and 0.90 for the four periods. Ellipse in (b) marks the areas where croplands predominate.



750 **Figure 5**. Spatial distribution of (a) mean annual GPP, (b) linear trend of annual GPP; and (c) spatially averaged annual GPP anomaly, during 2002-2014. Red lines show the annual trends in different periods. Dashed red lines show statistically insignificant trends. The coefficient of determination is 0.65, 0.99, 0.99 and 0.90 for the four periods. Ellipse in (b) marks the areas where croplands predominate.

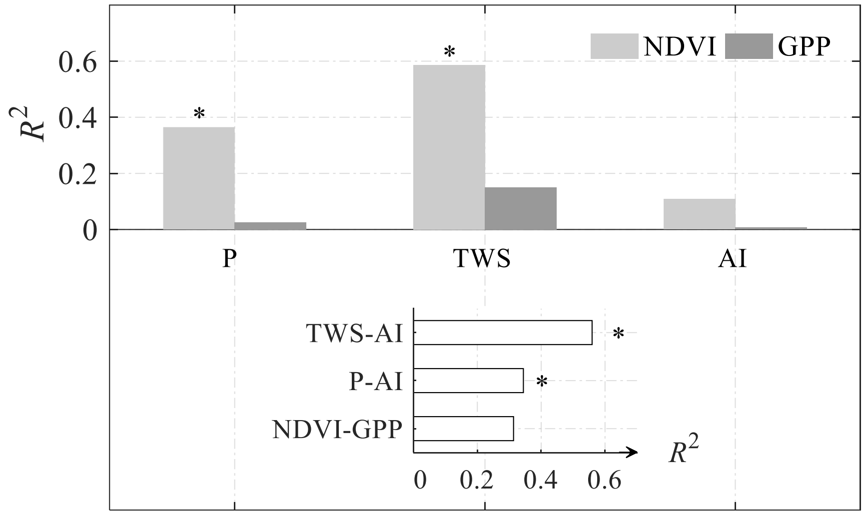
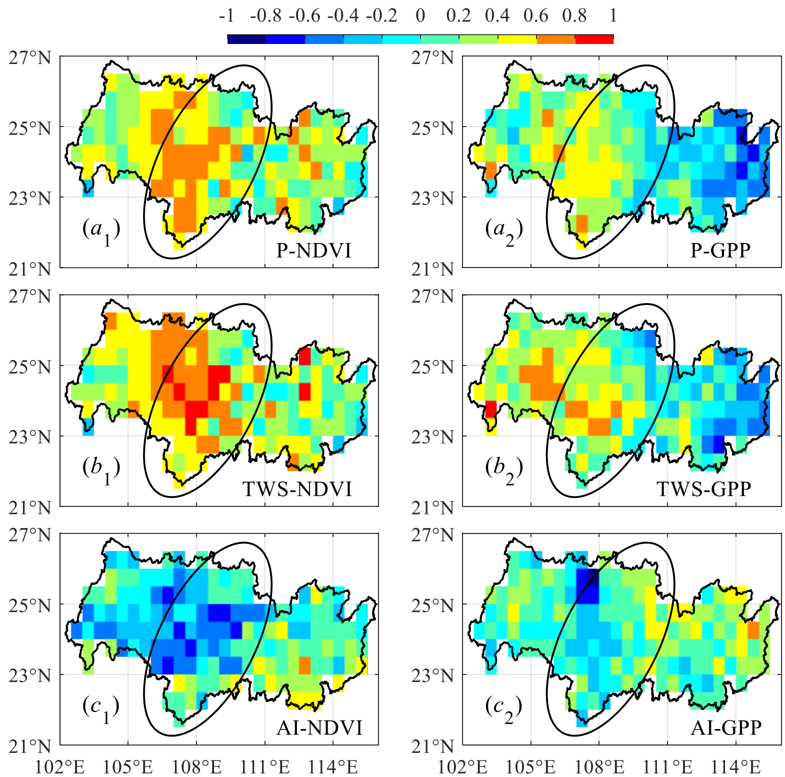


Figure 6. Coefficient of determination (R^2) from linear regressions between the anomalies of P, TWS, AI, NDVI and GPP at the annual scale. Asterisk indicates p<0.05.



760 **Figure 7**. Pearson correlation coefficient between annual anomalies of (a_1-a_2) precipitation, NDVI and GPP; (b_1-b_2) total water storage, NDVI and GPP; and (c_1-c_2) aridity index, NDVI and GPP. Ellipse marks the areas where croplands predominate.

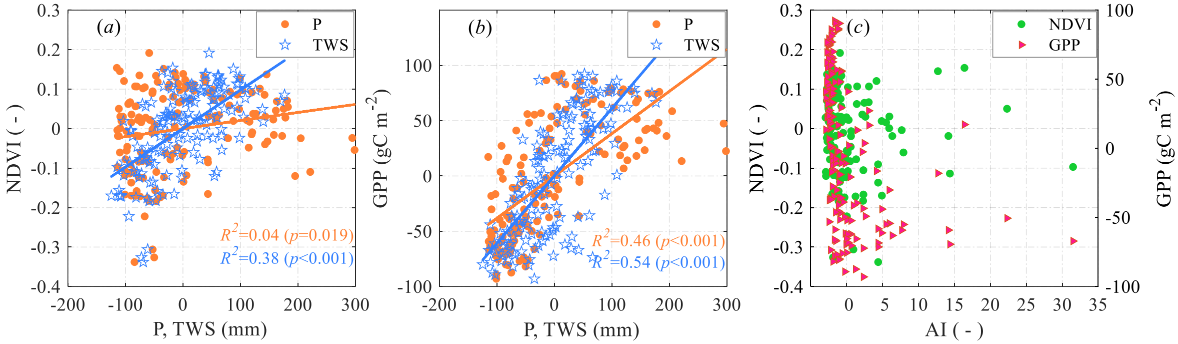


Figure 8. Scatter plot of monthly anomalies of precipitation (P), total water storage (TWS), aridity index (AI), NDVI and GPP.

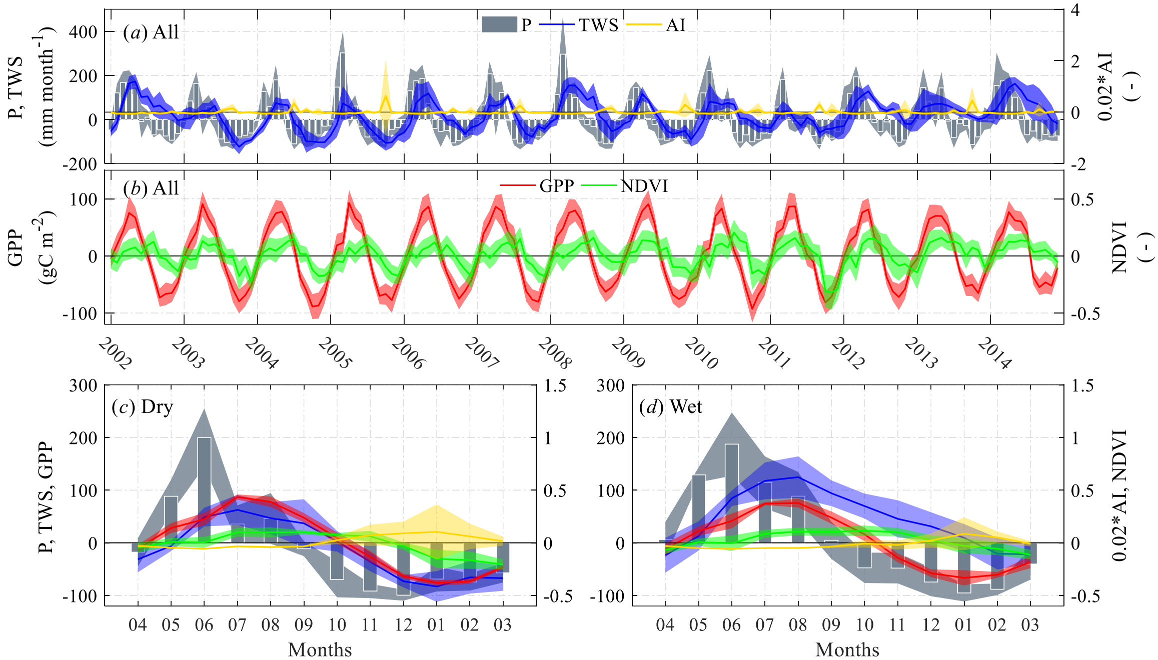
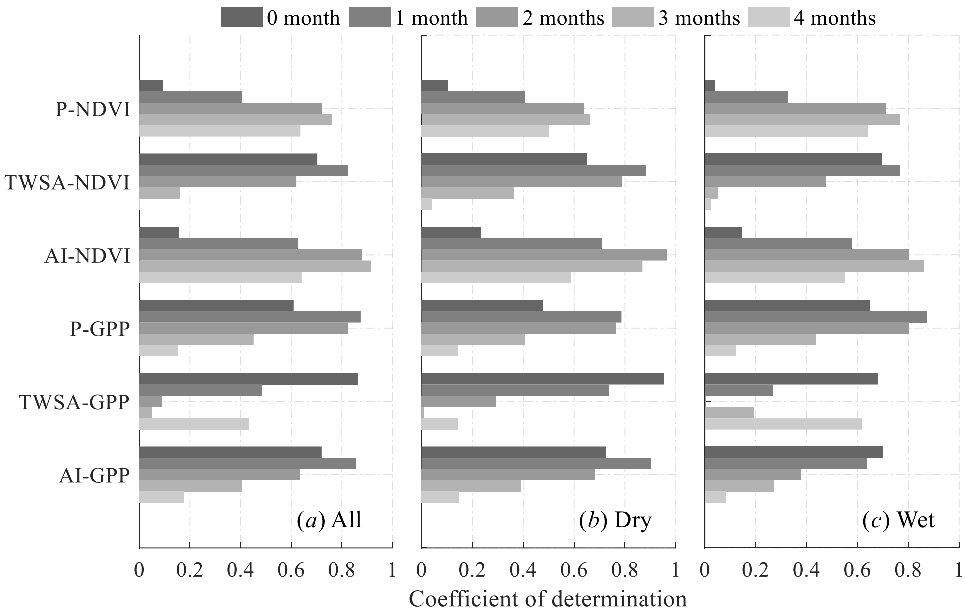


Figure 9. (a-b) Monthly variations of anomalies of precipitation (P), total water storage (TWS), aridity index (AI, scaled for a better view), and NDVI, gross primary production (GPP) in all years; (c) monthly means of dry hydrological years and (d) monthly means of wet hydrological years during 2002-2014. Plots *c* and *d* share the same units and legends with plots *a* and *b*. Shaded areas show the standard errors of each variable.



775 **Figure 10.** Coefficient of determination between monthly anomalies of precipitation (P), total water storage (TWS), aridity index (AI) and NDVI and GPP in (a) all years, (b) the dry years, and (c) the wet years after shifting different number of months.