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# 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 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 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 P on vegetation in wet years was stronger than dry years, while the TWS impact was stronger in dry years than wet years; moreover, greenness responded faster and productivity slower to 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 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 results in numerous ecohydrological problems such as droughts, flooding, tree mortality, etc., managing land use especially vegetation cover has been considerably practiced in many catchment planning projects (Adhami et al., 2019; Stewardson et al., 2017). The theoretical basis is that vegetation can intercept precipitation by the canopy which helps with flood control (Soulsby et al., 2017; Wheater and Evans, 2009); uptake soil water or groundwater and transpire it through leaves to increase moisture in the air; 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

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photosynthesis to accumulate biomass production and reduce greenhouse gas concentration (Notaro et al., 2007; Yosef et al., 2018). In turn, atmospheric and hydrologic conditions can affect vegetation health by altering vegetation physiological characteristics (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 rich literatures that examine the plant responses such as stomatal opening/closure to stress induced by both atmospheric condition and water supply (Martin-StPaul et al., 2017). For instance, plant water use responded sensitively to rainfall pulses in dry semi-arid areas (Huang and Zhang, 2015; Plaut et al., 2013), whilst the light exposure (i.e. energy) between frequent low-intensity rainfall events seemed more important to stimulate transpiration than rainfall itself in some humid low-energy boreal regions (Wang et al., 2017). Soil water especially the root-zone moisture plays a key role in 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) 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 many vegetation types and with different structures from site-specific analysis (Aranda et al., 2012; Wang et al., 2008). This would weaken the applicability of research outcomes on vegetation related ecological projects 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). Assessing and mitigating climate change impacts such as floods and droughts (Fowler et al., 2019; Ma et al., 2015) require integrated efforts at a catchment scale. From this perspective, it is necessary to investigate the plant-water relations at a larger scale beyond field sites.

Remote sensing (RS) products provide abundant information on land surface hydrology and vegetation characteristics and can be beneficial in overlooking the plant-water relations from a large spatial area. 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 phenology 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 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 in assisting the land and water management by pinpointing the hotspots for these changes and interactions.

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; on the other hand, vegetation are effective conduits to return water to the atmosphere, and 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

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related to water availability (Yu and Wang, 2012). Meanwhile, 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 ecosystems are sourcing soil water recharged by precipitation or groundwater, therefore, plant water use varies largely 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 majority of such studies were carried out in semi-arid regions because of the urgent need to find an equilibrium between ecological restoration and water resources in these water-limited areas. However, in the humid or semi-humid areas with abundant rainfall, it is still unclear whether the restriction of water on vegetation or the consumption of water by vegetation prevails in the long term.

Despite previous studies examining the changes in hydrologic compartments, climate change and vegetation, there are few insightful studies quantifying how hydroclimate and vegetation greenness and productivity interact at different time scales and under contrast dryness conditions in the subtropical Pearl River Basin in China over the recent 2 decades. Thus, this study is the first attempt to reveal the plant-water relations at a large spatial scale in the basin. Specifically, the objectives include (1) characterizing the spatiotemporal patterns of hydroclimate and vegetation change in the last 13 years or so, and identifying the hotspots for the changes; (2) quantifying the plant-water relations at different temporal scales under different dryness conditions; 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), 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 gradient of ~3000 m.

The dominant vegetation is forest of evergreen 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).

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

To assess the plant-water relations at a large spatial scale, we obtained hydroclimate and vegetation data from different sources. Precipitation (P) and potential evapotranspiration (ETp) were obtained from Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004); aridity index (AI) was then calculated as the ratio of ETp to P to represent the dryness condition. 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). 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.

Vegetation data in this study include Normalized Difference Vegetation Index (NDVI) and Gross Primary Production (GPP). NDVI was obtained from the GIMMS project during 04/2002–03/2015 and resampled to 0.5° using the nearest neighbor method and averaged to monthly to match the spatiotemporal resolution of GRACE and GLDAS data. Monthly GPP was obtained from the Numerical Terradynamic Simulation Group in the University of Montana and rescaled to 0.5° (Running et al., 2004). 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).

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. Furthermore, a lag effect analysis was carried out to determine the temporal dependency between variables where the linear relationship was not obvious.

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 anomalies of TWS, NDVI and AI under the criteria that dry conditions correspond to negative anomaly values of TWS and NDVI in addition to high anomaly of AI. Then the relationships between hydroclimate dynamics and vegetation greenness and productivity were specifically analysed. Uncertainties of the data used were estimated by the standard error of each variable at the monthly and annual scales.

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## 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% 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. 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 by 6.8 mm $yr^{-1}$ inferred by $GARCE_{JPL}$ and 4.6 mm $yr^{-1}$ by $GRACE_{CSR,}$ with an average of 5.9 mm $yr^{-1}$. 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. In the following sections, only the mean TWSA from $GRACE_{JPL}$ and $GRACE_{CSR}$ was used for analysis.

Figure 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. Although dryness condition has not changed significantly over the 13 years with an overall positive trend in space (0.004±0.012) and time (0.007), it has some interesting characteristics such as the drying tendencies primarily located in the southern areas, and the alternate periodical wetting and drying episodes temporally like TWSA. Areas with low TWS change rates 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%) 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 an 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 ($p$=0.56) with interannual fluctuations. It 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. Interestingly, in 2004 when water storage continued to decrease following the previous years, NDVI did not show a

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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, 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. 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 ($R^2$=0.12, $p$=0.257), which may imply a more direct and stronger impact of water stress on vegetation greenness than productivity 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 (35.9%, $p$=0.031) and AI (15.0%, $p$=0.191). Influence of these three variables on GPP followed the same order ($R^2$=0.12, 0.09, 0.02) but not statistically significant ($p$>0.05). In addition, GPP was positively associated with NDVI ($R^2$=0.17, $p$=0.163), and P and TWS were negatively correlated with dryness.

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 areas, and dryness more negatively affected greenness than productivity in these areas (Fig. 7). These analyses indicate that 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). This means that the water restriction on vegetation outweighed the water consumption by vegetation. 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

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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 NDVI and GPP was 32.8% and 8.4% higher on average in dry years than wet years, mainly attributable to the difference in the non-growing seasons from October to March. Both the minimum and maximum NDVI were lower in dry years than in wet years, particularly, the minimum NDVI in dry years was 87.4% lower than that in the wet years, compared to 8.6% lower for the maximum. GPP was similar in dry and wet years, with only 9.8% and 6.9% lower in dry years for minimum and maximum values, respectively. This implies that vegetation greenness is more sensitive to any changes in hydroclimate than productivity. Moreover, GPP in non-growing seasons in dry years was relatively higher than that in wet years reflecting a positive effect of stress on biomass accumulation.

Figure 10 gives the $R^2$ from linear regression between different variables considering phase shift for lag analysis. 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, 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 dryness can stimulate biomass production to some degree. 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. 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 (Mo et al., 2016; Wang et al., 2016). Here we also compared the GLDAS P with the measured P in the pixels where stations are available (Fig. 11). 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 underestimated observations by ~10% over all valid pixels. The comparison provides some confidence in applying the GLDAS products for long-term hydrological trend analysis, though discrepancies exist in the absolute values.

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

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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. (2014c) 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. 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). Despite the dispute of data accuracy, MODIS GPP seems more frequently used due to its moderate spatiotemporal resolution and data coverage.

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.

### 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 years NDVI and GPP showed insignificant changes 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 (Chen et al., 2015). Even so, 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, changes of TWS, NDVI and GPP jointly imply that the water storage increase in this hotspot region has resulted in the intensification of agricultural activities and boosted the food production since the early

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2000s. 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 informative for a possible shift of China's main food production from the north to the south in the context of water 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. 6), 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 by P, in comparison to the strong response of 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 1 month shorter than NDVI versus P and TWS. 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), which may imply that a certain degree of drying can stimulate biomass accumulation. This phenomenon is similar to the principle of regulated irrigation in agriculture to increase water use efficiency under a certain degree of water stress (Chai et al., 2016), and also revealed by other studies (Zhang and Zhang, 2019). 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 rain-abundant region instead of water shortage resulted from vegetation establishment.

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. (2014b) 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. 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

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increases in temperature and insignificant changes in precipitation in the basin which would trigger more heatwave induced flash droughts (Li et al., 2020). 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 but not overall significant. 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 dryness on vegetation production. 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; the processed data can be obtained from the corresponding author on request.

## Author contribution

Wang: Conceptualization, Methodology, Writing – original draft; 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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530 **Table 1**. Information of data used in this study

| | Product | Resolution | Time span | Source |
|---|---|---|---|---|
| **P, ETp** | GLDAS-Noah (v2.1) | 0.25°×0.25°, Monthly | 04/2002–03/2015 | https://disc.gsfc.nasa.gov |
| **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 | 04/2002–03/2015 | www.ntsg.umt.edu/project/modis/mod17.php |

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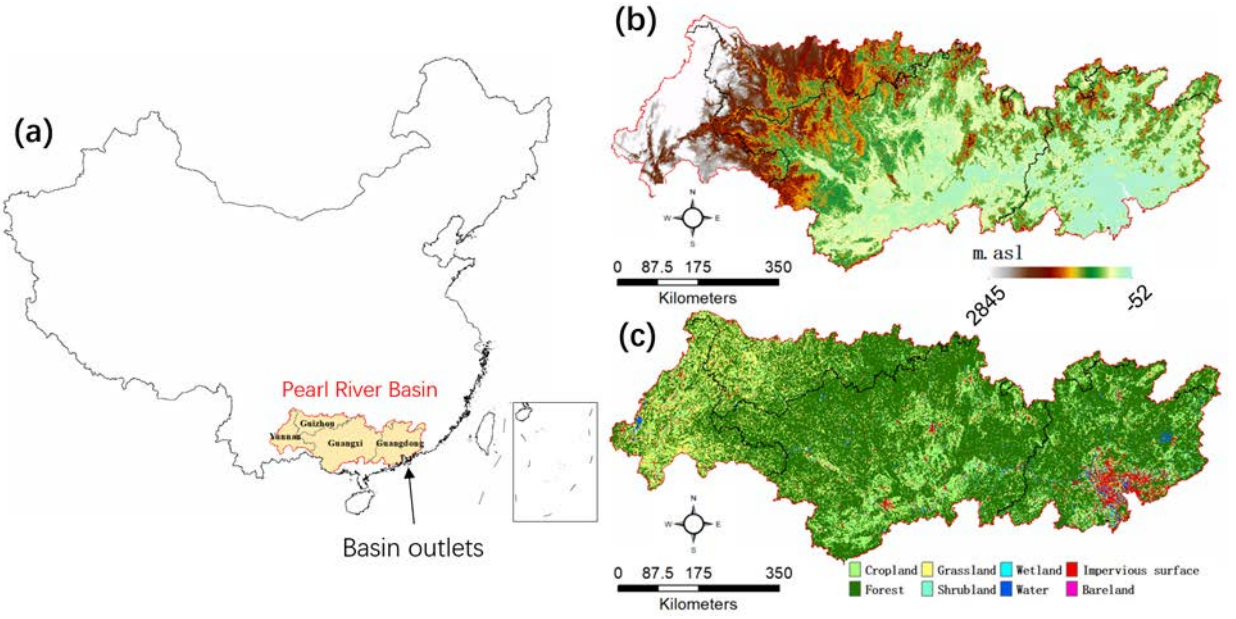


**Figure 1**. (a) The Pearl River Basin and the related provinces on the map of the China, (b) Digital elevation map (m.a.s.l, 535 1000 m resolution), and (c) Land cover types (30 m resolution).

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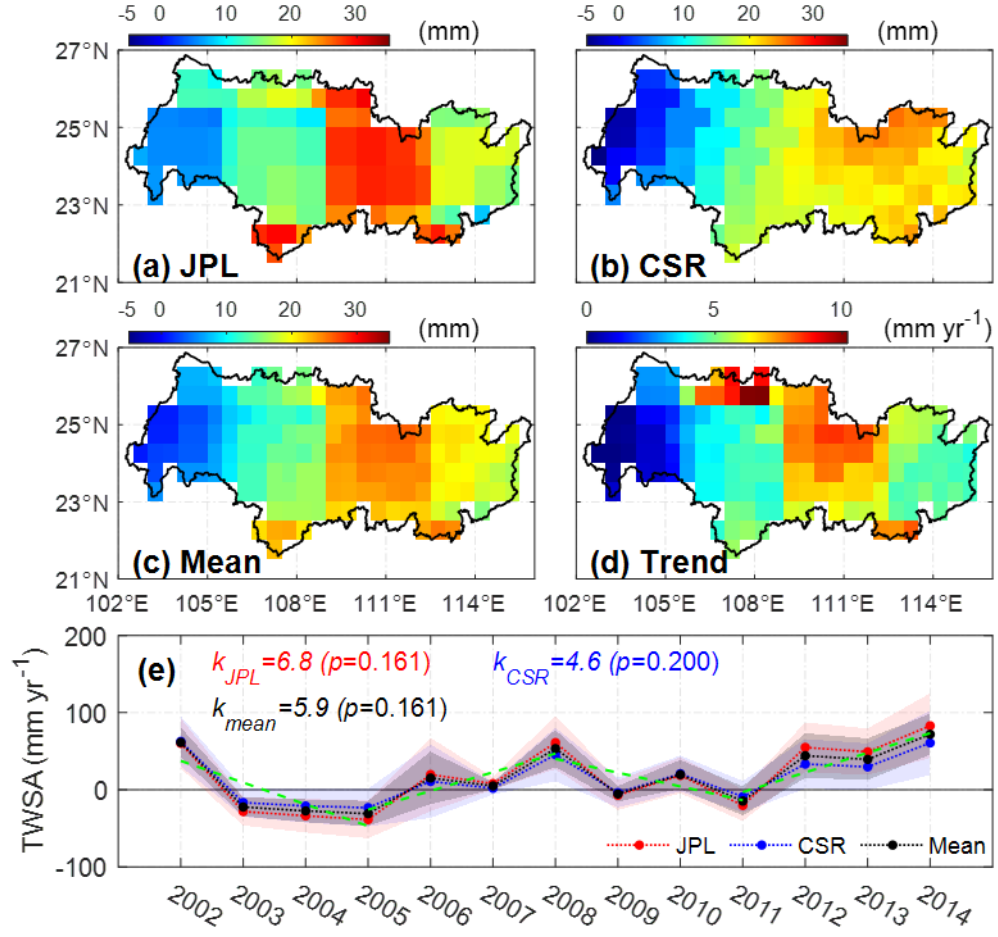


**Figure 2.** Spatial distribution of TWSA in the basin inferred by (a) $GRACE_{JPL}$, (b) $GRACE_{CSR}$, (c) the mean of $GRACE_{JPL}$ and $GRACE_{CSR}$, (d) the linear trends of the mean annual TWSA, and (e) mean annual TWSA over the entire basin. Shaded areas in (e) show the standard error of each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

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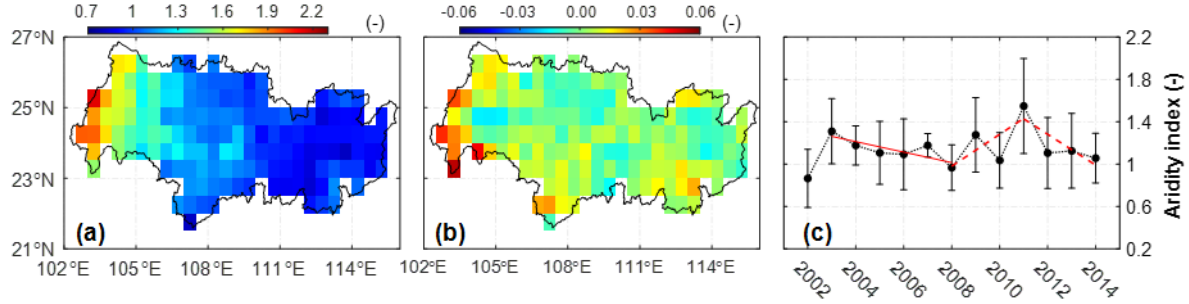


**Figure 3**. (a) Spatial distribution of the mean annual aridity index across the basin during hydrological years 2002-2016, (b) annual trend of aridity index, and (c) mean annual aridity index over the basin. Red lines show the periodical trends. Dashed red line indicates statistically insignificant trend. The coefficient of determination is 0.66, 0.54 and 0.68, respectively.

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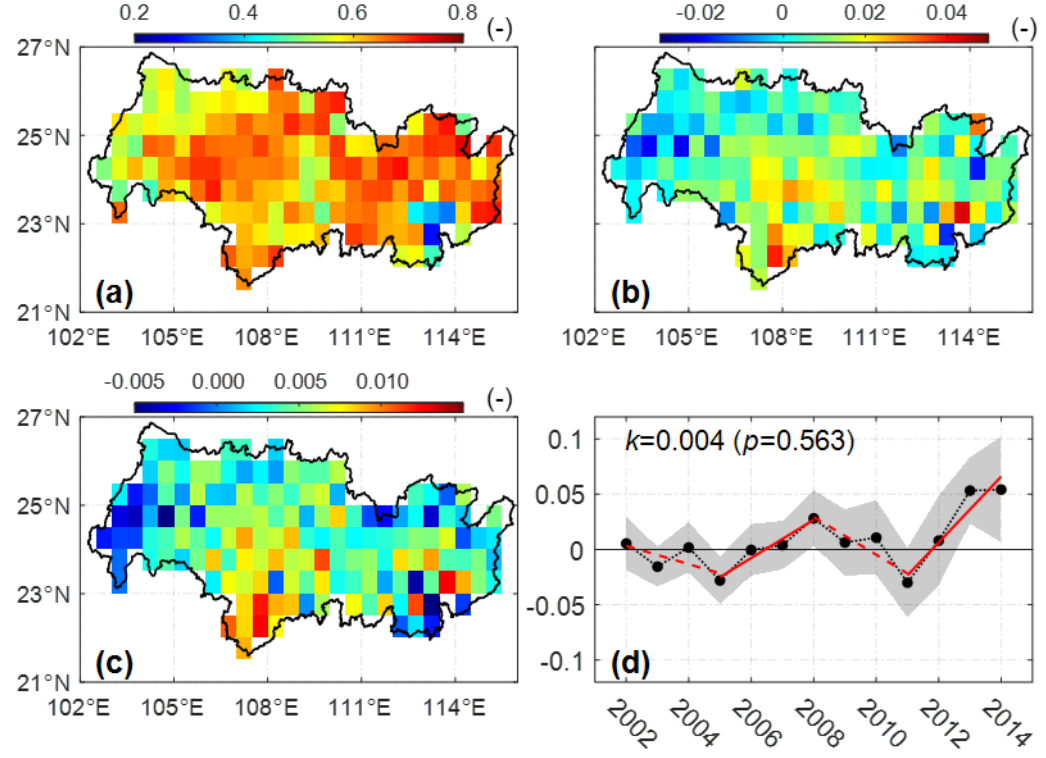


**Figure 4**. Spatial distribution of (a) mean annual NDVI, (b) mean annual NDVI anomaly, (c) linear trend of annual NDVI anomaly; and (d) spatially averaged annual NDVI anomaly, during 2002-2014. Red lines show the annual trends in different periods. Dashed red lines show statistically insignificant trends ($p$>0.05). Coefficient of determination is 0.47, 0.94, 0.81 and 0.90 for the four periods.

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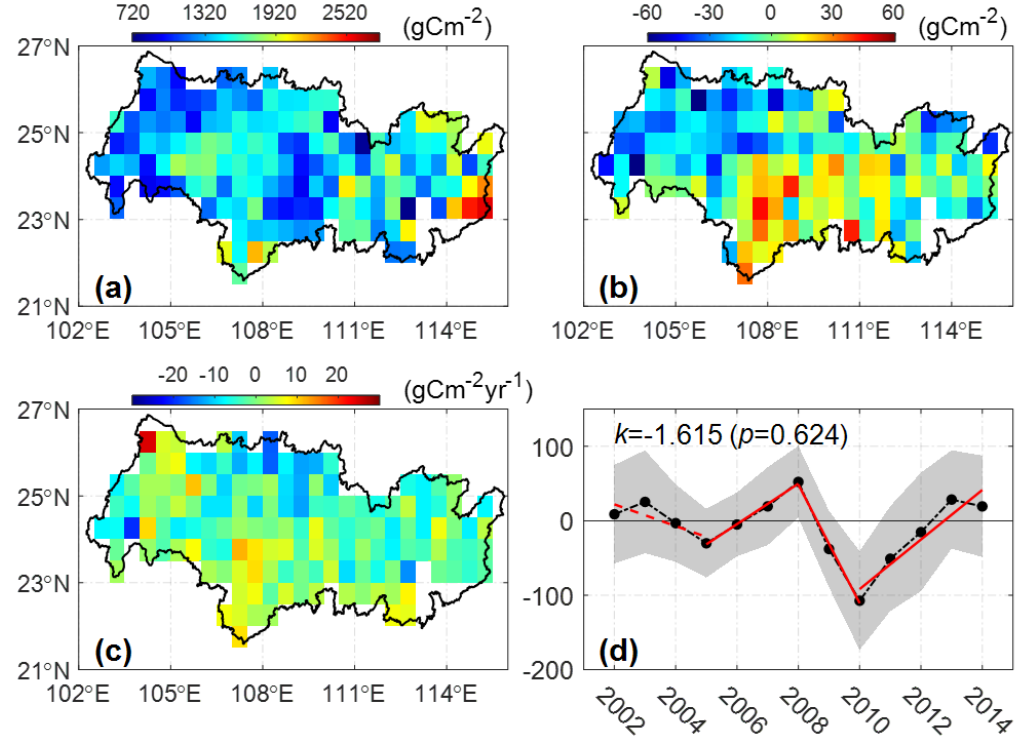


555 **Figure 5**. Spatial distribution of (a) mean annual GPP, (b) mean annual GPP anomaly, (c) linear trend of annual GPP anomaly; and (d) spatially averaged annual GPP anomaly, during 2002-2014. Red lines show the annual trends in different periods. Dashed red lines show statistically insignificant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

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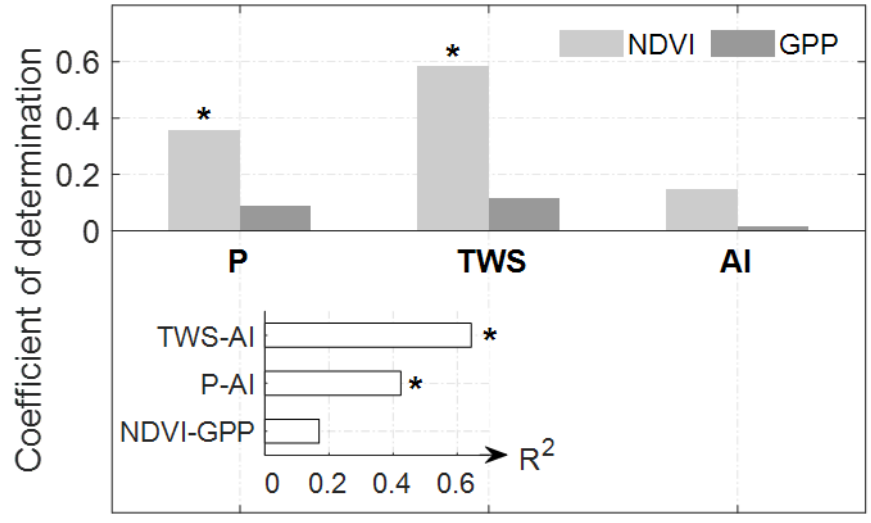


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**Figure 6**. Coefficient of determination ($R^2$) from linear regressions between the anomalies of P, TWS, AI, NDVI and GPP at the annual scale. Asterisk indicates $p<0.05$.

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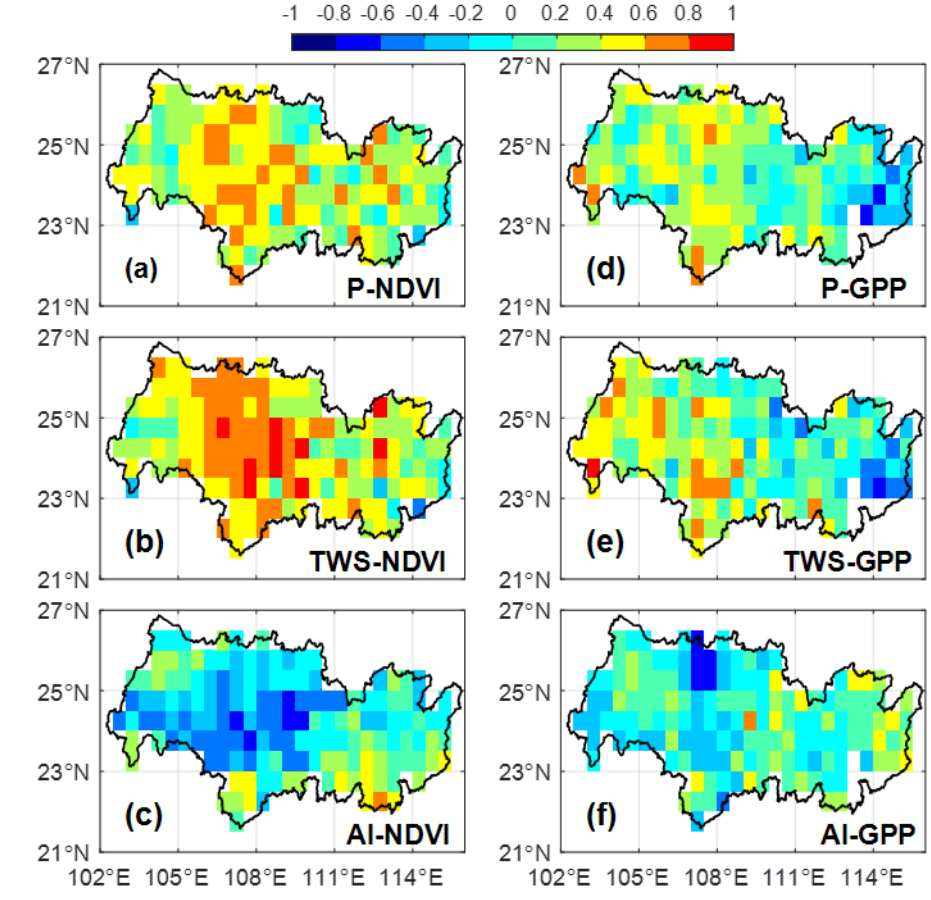


565 **Figure 7**. Pearson correlation coefficient between annual anomalies of (a-c) precipitation, total water storage, aridity index and NDVI; and (d-f) precipitation, total water storage, aridity index and GPP.

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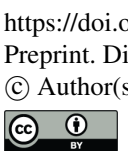

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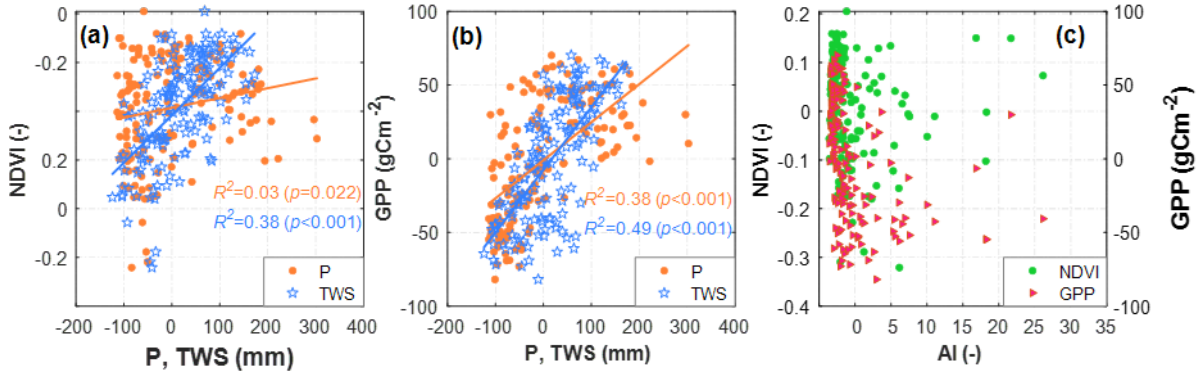


**Figure 8**. Scatter plot of monthly anomalies of precipitation (P), total water storage (TWS), aridity index (AI), NDVI and GPP.

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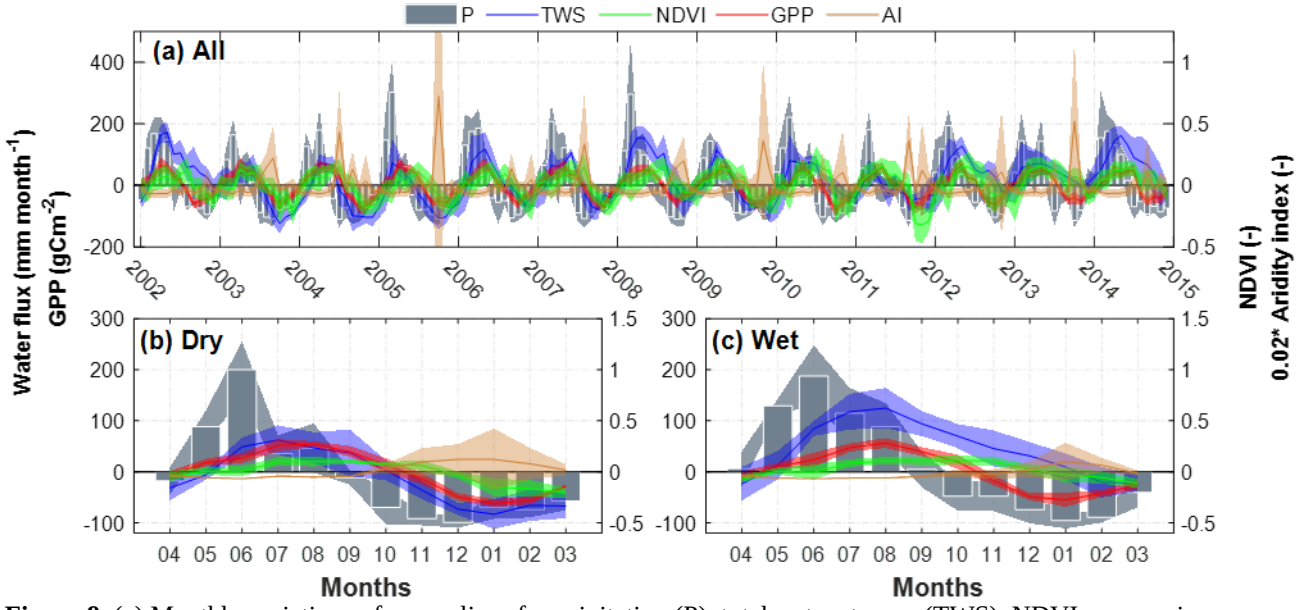


**Figure 9**. (a) Monthly variations of anomalies of precipitation (P), total water storage (TWS), NDVI, gross primary production (GPP) and aridity index (AI, scaled for a better view) in all years; (b) monthly means of dry hydrological years and (c) monthly means of wet hydrological years during 2002-2014.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

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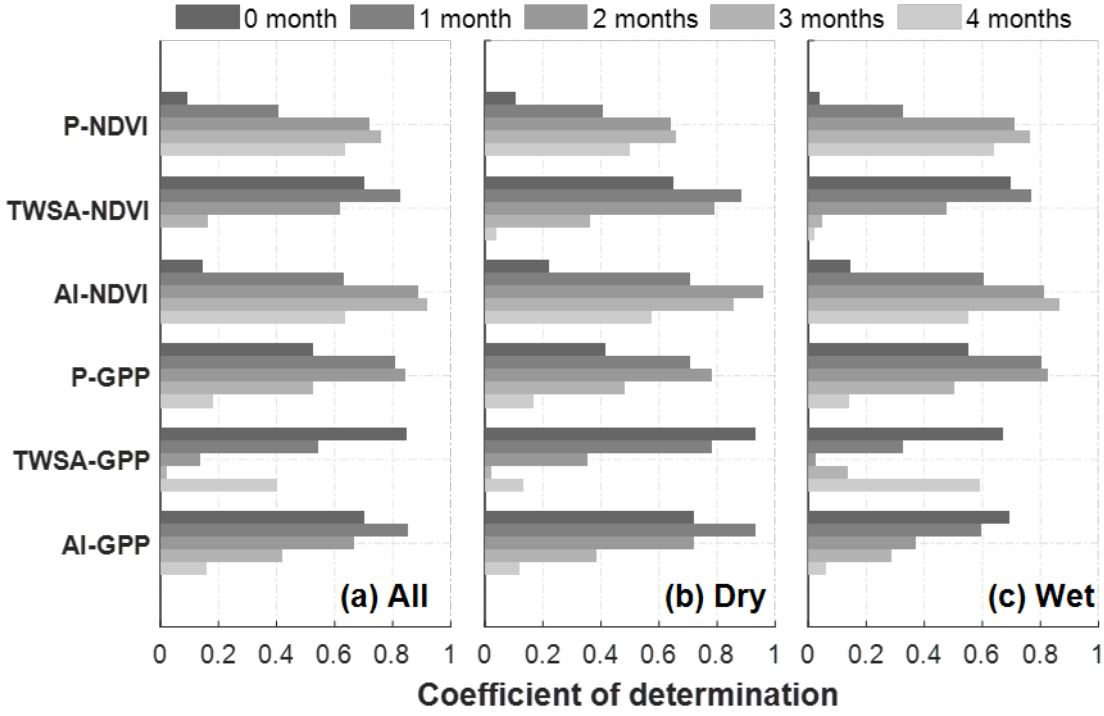


**Figure 10.** Coefficient of determination between monthly anomalies of precipitation (P), total water storage (TWS), aridity index (AI) and NDVI and GPP in (a) all years, (b) the dry years, and (c) the wet years after shifting different number of months.

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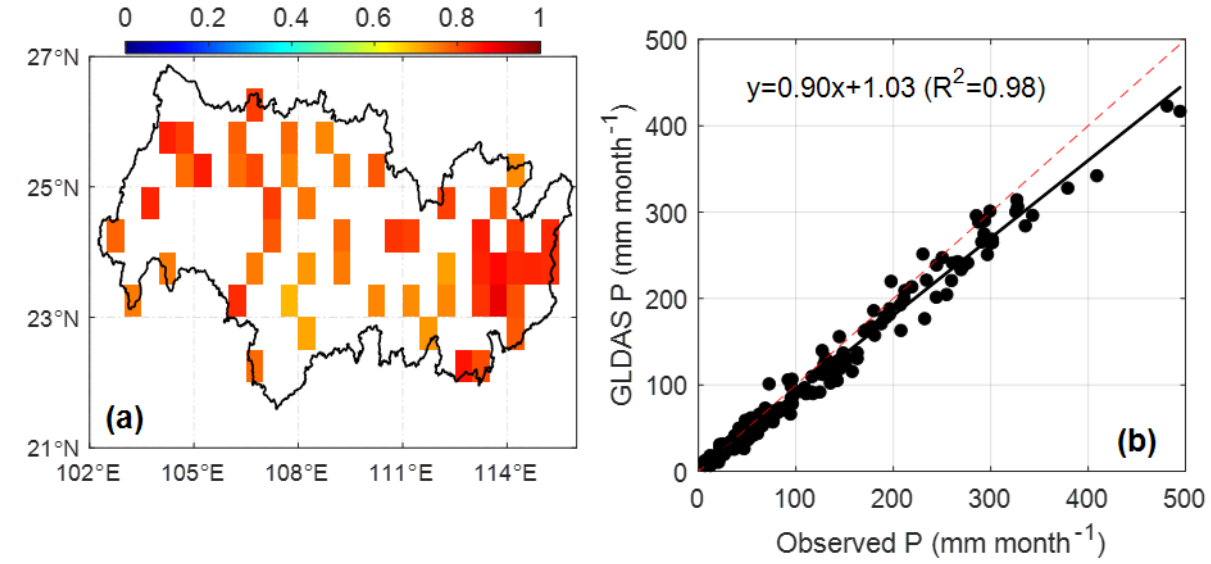


**Figure 11**. (a) Spatial distribution of $R^2$ between precipitation (P) from GLDAS and observations, and (b) scatter plot of monthly mean P over all pixels with stations available.

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