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Human imprint of water withdrawals in the wet environment: A case study of declining groundwater in Georgia, USA

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ABSTRACT

Study region: Georgia in the Southeast USA.
Study focus: The 'water-rich' Southeast USA has long been thought to be immune to climate change effects, leading to unsustainable water withdrawals practices. This study analyzed the impact of climate change and human activities, e.g., irrigation on groundwater trends at 43 monitoring wells from 1981 to 2017 in four distinct hydrogeologic provinces of Georgia, USA. We have corroborated the groundwater trend analysis with the surface water and climate trend analysis.
New hydrological insights: The deep confined Coastal Plain and Floridan aquifer systems show statistically significant declines in groundwater level. By contrast, the Surficial aquifer system shows relatively neutral trends over the same period. The water table in the shallower aquifers corresponds closely to the changes in the precipitation and streamflow trends. A declining secular trend in the deeper confined aquifer is potentially attributable to the irrigation water withdrawals in Georgia.

1. Introduction

Groundwater is an important natural resource and is an integral part of the global freshwater supply (Gurdak et al., 2009). In the United States, groundwater is responsible for up to 40 percent of the freshwater supply, with as many as 40 million people consuming groundwater (Alley et al., 1999; Gurdak et al., 2009). Many principal aquifers around the country are in danger of depletion due to climate change and human withdrawals (Brekke, 2009). Previous studies have found depleted groundwater aquifer mainly in semi-arid to arid climates, e.g., the Central Valley aquifer, California (Miller et al., 2009). The High Plains aquifer (Ogallala aquifer) that covers more than 450,000 km^2 in eight states of the central United States has shown a continual decline in water table since the 1950s; in some areas, the drop is 50 m or higher (Sophocleous, 2010).

The 'water-rich' Southeast USA (Fig. 1) has long been thought immune to anthropogenic climate effects on surface and groundwater (Ingram et al., 2013; NWF, 2008). The Southeast USA typically has high amounts of annual precipitation (1.9 to 1.4 m on average), and its interannual variability is linked to the El-Nino and Southern Oscillation Index (ENSO) (Ford and Labosier, 2014; Labosier and Quiring, 2013; Newman et al., 2016). Extreme rainfall events measured using the number of days with 3 in. or more rainfall in a year have increased; and climate model projections show intensification of the Southeast's hydrologic cycle (Karl et al.,

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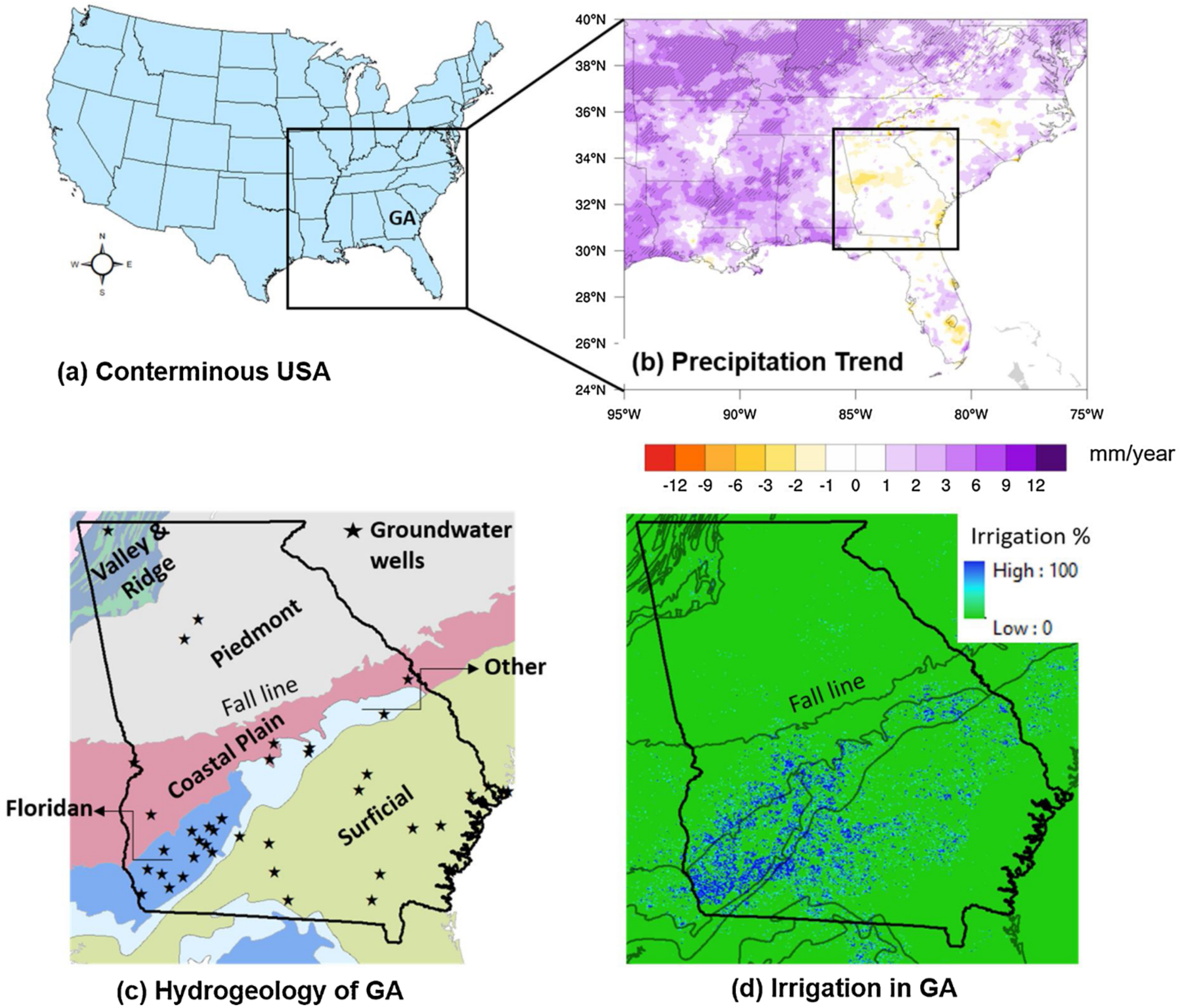

Fig. 1. Geography, climate, and hydrogeology of the study area. (a) the conterminous USA with Georgia (GA) located in Southeastern USA, (b) Long-term precipitation trend (mm/year from 1951 to 2015) in the Southeastern USA, hatching shows the statistical significance of trends at 95 % confidence level and (c) major aquifers systems surface outcroppings (other refers to areas of multiple units or undifferentiated rock), and groundwater monitoring wells in Georgia, and (d) The irrigation intensity map that shows % of grid-cell (1 km × 1 km) irrigated based on remote-sensing based data (see text).

2009; Kumar et al., 2015; Kunkel et al., 2013b; Melillo et al., 2014).

Over the last 60 years, the Southeast USA experienced a nearly 40 % larger population increase than the rest of the USA (Terando et al., 2014). The 12 states comprising Southeast population(Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia) are expected to grow by 29 % from 2010 to 2040 (https://demographics.coopercenter.org/). Georgia's population is expected to grow by 24 %. The land-use patterns are changing; for example, the urban area has increased by 200 % from 1945 to 1992 (Sun et al., 2008; Wear, 2002). The water demands have risen due to urban growth and irrigation expansion (Georgakakos et al., 2010). According to Painter (2019), overall water use in Georgia has declined almost 50 % since 1980 due in large part to declining surface water withdrawals (90 % of total reduction) and decreasing thermoelectric power cooling use (78 % of total reduction). The period from 1980 to 2000 showed an overall increase in water use with up to 159 % increase in irrigation water use from 1990 to 2000 (Painter, 2019). Water use for irrigation, primarily through groundwater withdrawals in the southern portion of the state, is the largest use of groundwater in recent years (Painter, 2019). In Georgia, acres irrigated have increased roughly 2,000 % from 42,408 acres to 936,245 acres from 1976 to 2013 (Williams et al., 2017). High levels of irrigation have been shown to cause aquifer storage loss, changes in groundwater flow, i.e., gaining stream to losing stream, decreases in stream baseflow and decreases in aquifer recharge (Mitra et al., 2016, 2019).

Although the hydrogeological characteristics of major aquifers in the Southeast have been investigated (e.g., Miller, 1986; Hicks et al., 1987; Johnson and Bush, 1988; Davis, 1996; Williams and Dixon, 2015; Self-Trail et al., 2019), the effects of climate variability and land-use change on groundwater decline and its relationship with hydrogeological characteristics is an active research area. The sub-seasonal to inter-annual groundwater variability is mostly explained by climate variability (Almanaseer and Sankarasubramanian, 2012; Humphrey et al., 2016). However, long-term declining trends are attributed to the anthropogenic water abstraction in several regions, e.g., northwest India and the Middle East (Humphrey et al., 2016; Rodell et al., 2009; Voss et al., 2013). Scanlon et al. (2012) found that a higher pumping rate than the recharge rate has resulted in a continual decline in groundwater in the central and southern high plains. Shamsudduha et al. (2009) have attributed a declining water table (0.5 m–1 m per year) to urbanization and dry season rice cultivation in Bangladesh.

Hydroclimatic time series show long-term persistence (LTP), the clustering of wet or dry periods for several years, also known as the Hurst phenomenon (Hurst, 1956; Iliopoulou et al., 2018; Koutsoyiannis, 2003). This is especially the case with groundwater data that shows a higher persistence than the precipitation (shown later). Bloomfield and Marchant (2013) found a positive correlation between site-dependent LTP and groundwater drought's length that can lead to a reduction in streamflow (Hughes et al., 2012). However, the effects of LTP on the statistical significance of groundwater trends are not investigated. The LTP presents a significant source of uncertainty that leads to an underestimation of variance in the time series and, therefore, can lead to a false identification of significant trends (Koutsoyiannis and Montanari, 2007). We employ a nonparametric trend detection technique that accounts for the long-term persistence in the time series, as documented in our earlier work (Kumar et al., 2009). Robust identification of significant trends is helpful to investigate their drivers outside the natural variability realm (Banerjee et al., 2017; Kumar et al., 2013b; Singh et al., 2020).

Overall, we identify two knowledge gaps: (1) effects of LTP on groundwater trend's significance, (2) the relationship among groundwater trends, hydrogeological characteristics, and anthropogenic drivers for Georgia's aquifer system. We address the knowledge gaps using a large dataset and advanced statistical techniques. A total of 404 USGS groundwater monitoring wells have been collected, out of which 43 wells had long-term daily data availability for the recent historical period (1981–2017) and were analyzed for the changes in the water table. A dataset of this size allows us to assess the role of natural and anthropogenic forcing (e.g., land-use change and irrigation) by testing the hypothesis that "***effects of climate change on groundwater trends depend on the hydrogeological characteristics of the aquifer system. The deviation from the climate variability can potentially be attributed to the anthropogenic causes,*** *e.g.*, ***irrigation expansion in the region***". We organize this research as follows: Section 2 describes the study area, data, and methods, including discussion about the hydrogeological characteristics, data processing, and nonparametric trend detection technique. We present results from the trend analysis in Section 3. We also explore the relationship of groundwater variability with surface water and climate variability in Section 3. Finally, we relate the hydrogeological characteristics with the persistence in the time series using seasonal autocorrelation analysis (Kumar et al., 2019). We present the discussion and implications of our findings in Section 4. The conclusion from this study is presented in Section 5.

2. Study area, data, and methods

2.1. Climate

Georgia, located in the Southeast USA, has a warm temperate climate, fully humid precipitation, and hot summer temperature (Kottek et al., 2006). Long-term annual mean precipitation has not changed significantly in the state (Fig. 1a). Historically, Georgia and the Southeast's average temperature showed no significant warming trend over the 20th century; no-warming trends are attributed to natural variability and industrial pollution that has declined in recent years (Banerjee et al., 2017; Kumar et al., 2013b; Kunkel and Angel, 2013a; Yu et al., 2014).

2.2. Aquifer description

The fall line divides the hydrogeology of Georgia with shallow unconfined aquifers in the north and generally confined aquifer in the south where most agriculture is located (Fig. 1b) (Williams and Kuniansky, 2016; Williams et al., 2017). Piedmont and Blue Ridge Provinces dominate the northern half; the aquifers here are typically unconfined and mostly composed of regolith or crystalline-rock aquifers which store water in fractures, joints, contacts, weathered zones, and other features (Clarke and Pierce, 1985; Gordon and Painter, 2018). The Valley and Ridge Province has thrusted and folded parallel ridges underlain by resistant sandstone, conglomerate, or cherty dolostone and valleys underlain by siltstone, shale, limestone, or other weathering prone rocks (Rutledge and Mesko, 1996). The groundwater is typically unconfined in joints, fractures, and solution openings (Clarke and Pierce, 1985). In this paper, Piedmont and Blue-ridge aquifer systems are lumped into one group: the Northern Aquifer System (NAS) due to the similarities of the aquifers and the lack of dense observation network (Fig. 1b).

The south of the fall line is comprised of three different aquifer systems: the Floridan aquifer system (FAS, carbonate rocks), the Coastal Plain aquifer system (CPAS, clastic rocks), and the Surficial aquifer system (SAS) (Fig. 1b) (Gordon and Painter, 2018; Williams and Dixon, 2015). Aquifers are typically confined except for the northern extent of the Coastal Plain and the surficial aquifer system (Clarke and Pierce, 1985). The Floridan aquifer system is one of the most productive in the US and is mainly used as the primary source of freshwater (Fanning and Trent, 2009; Miller, 1986). The Floridan aquifer system is separated into the Upper and Lower Floridan aquifers. The Upper Floridan aquifer is of Eocene to Oligocene aged limestone, dolomite, and calcareous sand (USGS, 2006). The Lower Floridan Aquifer is defined as the unit under the Middle Floridan Confining Unit, which is exposed at the surface in some portions of Southeast Georgia as part of the Floridan aquifer system (Miller, 1988). The Upper Floridan aquifer is confined in areas where it is overlain by siliciclastic sediments or a low-permeability Miocene aged limestone and is unconfined at surface outcrops at the northern extent of the aquifer and through karst features to the southwest and southcentral parts of Georgia (Miller, 1986; Williams and Dixon, 2015; Denizman, 2018). The aquifer thickens to the Southeast up to a maximum depth of around 500 m (Miller, 1986).

The Coastal Plain aquifer system is composed of a thick wedge of unconsolidated to poorly consolidated Jurassic to Holocene clastic rocks that dips to the Southeast from the Fall Line to the Atlantic Ocean (Renken, 1996). The Floridan aquifer system overlies the Coastal Plain aquifer system, and both are hydraulically interconnected laterally (Lower Floridan carbonates to the south, which grades into Coastal Plain clastics of the same age to the north) and vertically in the Upper Floridan (gradual gradations or interfingering between clastics and carbonates) and underlain by crystalline bedrock (Renken, 1996) (Fig. 2).

The surficial aquifer system forms a thin irregular blanket of the terrace and alluvial sands that overlies the Floridan aquifer system (Williams and Dixon, 2015). The surficial aquifer system acts as temporary groundwater storage that may ultimately recharge the underlying Floridan aquifer system (Williams and Kuniansky, 2016). Thus, we have divided groundwater well data into four major aquifer systems: (1) Floridan Aquifer System (FAS), (2) Coastal Plain Aquifer System (CPAS), (3) Surficial Aquifer System (SAS), and (4) Northern Aquifer System (NAS). The deep, confined aquifers in CAPS have a median depth of 194 m below the ground level. The FAS accounts for the maximum number of wells (27 out of 43) and has a median depth of 106 m. In contrast, the Surficial aquifer has a median depth of 8 m (Table 1).

2.3. Data

Georgia groundwater table data for 404 monitoring wells were collected from the United States Geological Survey (USGS) National Water Information System (NWIS). Daily water table measurements were obtained from the database for each well, for the period from 1951 to present; however, most of the wells did not have continuous daily measurements over this entire time interval. To include the most wells possible, 43 wells were determined to have 90 % or more data available over a time range from 1981 to 2017

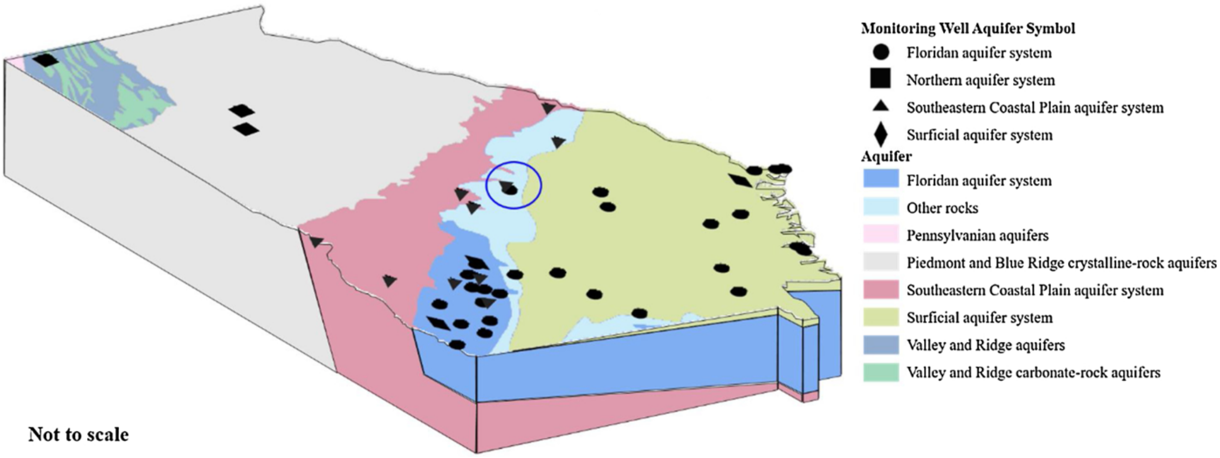

Fig. 2. The vertical and lateral interconnectivity of the aquifer systems in Georgia. A 3-D vertical cross-section and groundwater monitoring wells associated with the four major aquifer systems. Figure reproduced from USGS Fact Sheet 2006-3077 (USGS, 2006). Please note that the depth of the well determines its association with the aquifer system. For example, two nearby monitoring wells encircled in blue are withdrawing water one from Floridan, and another from the Coastal Plain aquifer system. Similarly, many wells (black filled circle) are geographically located in the Surficial aquifer system, but they are withdrawing water from the Floridan aquifer system. Each well's depths and corresponding association with the aquifer system is detailed in Supplementary Table 1.

Table 1
Hydro-geologic Aquifers in Georgia and groundwater trends. FAS – Floridan Aquifer System, CPAS – Coastal Plains Aquifer System, SAS – Surficial Aquifer System, and NAS – Northen Aquifer System. The number of monitoring wells, their median depths, and groundwater trends is shown. Statistical significance of trends at a 95 % confidence level is computed using the nonparametric Mann-Kendall test and considering long-term persistence (LTP) in the time-series. Ann_Mean: Annual average, Ann_Range: the difference between the 1-day maximum and 1-day minimum time series, Ann_Min: Annual 1-day minimum, and Ann_Max: Annual 1-day maximum time series.

Aquifer	Median depth (Min-Max) m.	Numbers of increasing/decreasing trends			
		Ann_Mean	Ann_Range	Ann_Min	Ann_Max
FAS (27)	106 (30–566)	2/8	8/3	2/10	1/7
CPAS (10)	194 (113–514)	0/4	5/0	0/7	0/7
SAS (3)	8 (5–12)	0/0	1/1	0/0	0/1
NAS (3)	104 (22–189)	0/1	1/1	0/1	1/1
State wide (43)	137 (5–566)	2/13	15/5	2/18	2/16

(Supplementary Table 1). All the wells used in this study are designated as monitoring wells, i.e., they are not used for human consumption and instrumentally record daily water table measurements. Other information retrieved from the NWIS database includes latitude and longitude for the station, name of the regional and local aquifer. The depth of the well typically determines their aquifer category; however, USGS aquifer classification was ultimately used as the determining factor for aquifer categorization such as in areas where the surficial aquifer was identified but the coastal plains aquifer is known to outcrop (Fig. 2 and Supplementary Table 1).

Additionally, we employed USGS surface water observation (streamflow) (Falcone et al., 2010), and high-resolution Parameter--elevation Regressions on Independent Slopes Model (PRISM) climate data to corroborate the groundwater analysis. Long-term streamflow observations at reference sites that have minimal human interference are not available in Georgia (Singh et al., 2020), hence we employed streamflow observations from non-reference sites. PRISM uses climate observations from a wide range of monitoring networks, applies quality control measures, and topography dependent spatial interpolation techniques to develop high-resolution (4-km) spatial climate datasets to reveal short-term and long-term climate patterns for the conterminous United States (Daly et al., 1994, 2008). We also used USGS's 2012 Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture 1-Kilometer Dataset to determine the irrigation extent in Georgia (Pervez and Brown, 2010) (Fig. 1b).

2.4. Metrics

Four groundwater statistics: annual average (Ann_Mean), 1-day minimum (Ann_Min), 1-day maximum (Ann_Max), and annual range: the difference between 1-day max and 1-day min were computed to capture the complete spectrum of groundwater change in Georgia. The annual range is a measure of reliability, an increasing trend in the annual range suggests less reliable groundwater availability, i.e., a higher groundwater table in the wet season, or the deeper groundwater tables in the dry season, or both (Kumar et al., 2014). The groundwater statistics were computed for each station, and each year using the daily data, then the annual time series were employed for the trend calculation using the nonparametric method.

We used the mean standardized departure (MSD) (Eq. 1) to average the time series of different groundwater wells in the given regions, and to compare the groundwater variation with the climate variations.

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

where X is the value being standardized, e.g., annual mean time series, μ is the mean of the distribution, and σ is the standard deviation of the time series. We standardize the time series locally, e.g. at each station then average it across the aquifer system or the state-wide. Hence, the standard deviation of averaged MSD can become smaller than one if the spatial variability or noise is greater, e.g. state average MSD of precipitation.

2.5. Nonparametric trend detection

We compute trends using the Theil-Sen method (Sen, 1968; Theil, 1992) (Eq. 2), and its significance is determined using nonparametric Mann-Kendall test (Kendall, 1975; Mann, 1945). If $x_1, x_2, \ldots\ldots\ldots, x_n$ is a time series (X) of given length n (in years), then magnitude of trend (TSA) is given as below:

$$TSA = median\left(\frac{x_j - x_i}{j - i}\right) for\ all\ i < j \tag{2}$$

The trend significance calculation accounts for long-term persistence in the time series, as described in our previous study (Kumar et al., 2009). The nonparametric method has the following advantages: (1) it contains no prior assumption about the linear trend, (2) it is more accurate in detecting trend (higher power) in non-normally distributed data, e.g., streamflow (Önöz and Bayazit, 2003; Yue et al., 2002), and (3) it is robust against outliers.

We determine LTP using the Hurst coefficient (H) (Hurst, 1951). The concept of the Hurst coefficient is based on the hypothesis that hydroclimatic time series (Xt) exhibit scale-invariant properties (Koutsoyiannis, 2003), i.e.

$$\left[Z_i^{(k)} - k\mu\right] \triangleq \left(\frac{k}{l}\right)^H \left[Z_j^{(l)} - l\mu\right] \quad (3)$$

Where $\triangleq$ represents equality in finite-dimensional joint distribution, μ is the expected value of X_t, $Z_i^{(k)}$ is the aggregated stochastic process at a scale k (an integer greater than 1) defined as

$$Z_i^k = \sum_{p=(i-1)k+1}^{ik} X_p \quad (4)$$

and $Z_j^{(k)}$ is the aggregated stochastic process at scale k, and H is the Hurst coefficient. For a stationary and positively correlated time series, H varies in the range (0.5, 1); H = 0.5 indicates independence, and increasing values of H represent increasing LTP intensities (Koutsoyiannis and Montanari, 2007). We estimated the Hurst coefficient from the detrended data as the maximum likelihood estimator of a fractional Gaussian noise process (Eq. 3) (Hamed, 2008). Non-Gaussian data can also follow the fractional Gaussian noise process (Koutsoyiannis, 2000, 2003). A full description of the application of the statistical methods is given in (Kumar et al., 2009). If H is statistically significant, then the variance of the time series is inflated empirically for statistical significance calculation using the nonparametric Mann–Kendall test (Hamed, 2008; Kendall, 1975; Mann, 1945). This methodology successfully identifies multi-decadal climate variability in the southeastern US (Kumar et al., 2013a).

A comparison with the short-term persistence (STP) model is shown in the Supplementary materials. The STP method calculates the statistical significance after trend-free pre-whitening of the time series, i.e., removing the influence of the lag1 autocorrelation from the detrended time series (Kumar et al., 2009; Yue et al., 2002).

2.6. Linear trend attribution

Following Humphrey et al. (2016), we divided total long-term variability (X_{long}) into linear (X_{lin})and inter-annual components (X_{inter}); where X_{long} is the annual time series. The X_{long} is same as the X time series discussed above because we use annual time series, i.e. sub-seasonal or seasonal variability are not investigated. We computed the inter-annual variability component from the detrended time-series $\left(x_{inter,i} = x_{long,\,i} - TSA * i\right)$and attributed the remainder to the linear trend as follows:

$$X_{long} = X_{lin} + X_{inter} \quad (5)$$

$$R_{lin} = 1 - \frac{\sigma^2_{inter}}{\sigma^2_{long}} \quad (6)$$

R_{lin} is the fraction of total variability explained by the linear trend component, where σ^2_{long} is the variance of X_{long} and σ^2_{inter} is the variance of X_{inter}.

2.7. Comparison with GRACE water storage anomaly

We performed time-series comparisons between groundwater anomaly data and NASA's total water storage anomalies data from Gravity Recovery and Climate Experiment (GRACE) satellite to understand spatial representativeness of our monitoring well results. The GRACE data measures variations in Earth's gravity field, which correlates with the regional changes in groundwater storage on Earth's surface (Landerer and Swenson, 2012; Swenson, 2012).

2.8. Memory time-scale of the aquifer system

We characterized the groundwater aquifers by their memory time-scale using seasonal autocorrelation analysis as described by Kumar et al. (2019). The autocorrelation function of a first-order Markov process also known as the red noise process is given below (Amenu et al., 2005; Chikamoto et al., 2015; Delworth and Manabe, 1988; Schlosser and Milly, 2002):

$$\rho(\tau) = \exp\left(\frac{-t}{\tau}\right) \quad (7)$$

Where ρ is autocorrelation function at a given lag t, and τ is the decorrelation (or *e*-folding) time scale, also known as the memory time-scale, i.e., the lag at which the autocorrelation function becomes statistically indistinguishable from zero.

3. Results

3.1. Regional climate trends

The Southeast USA has become wetter (Fig. 1b) as expected from the wet-gets-wetter paradigm and under the climate change scenario (Held and Soden, 2006; Kumar et al., 2015). However, there are regional variations, e.g., Georgia did not experience a

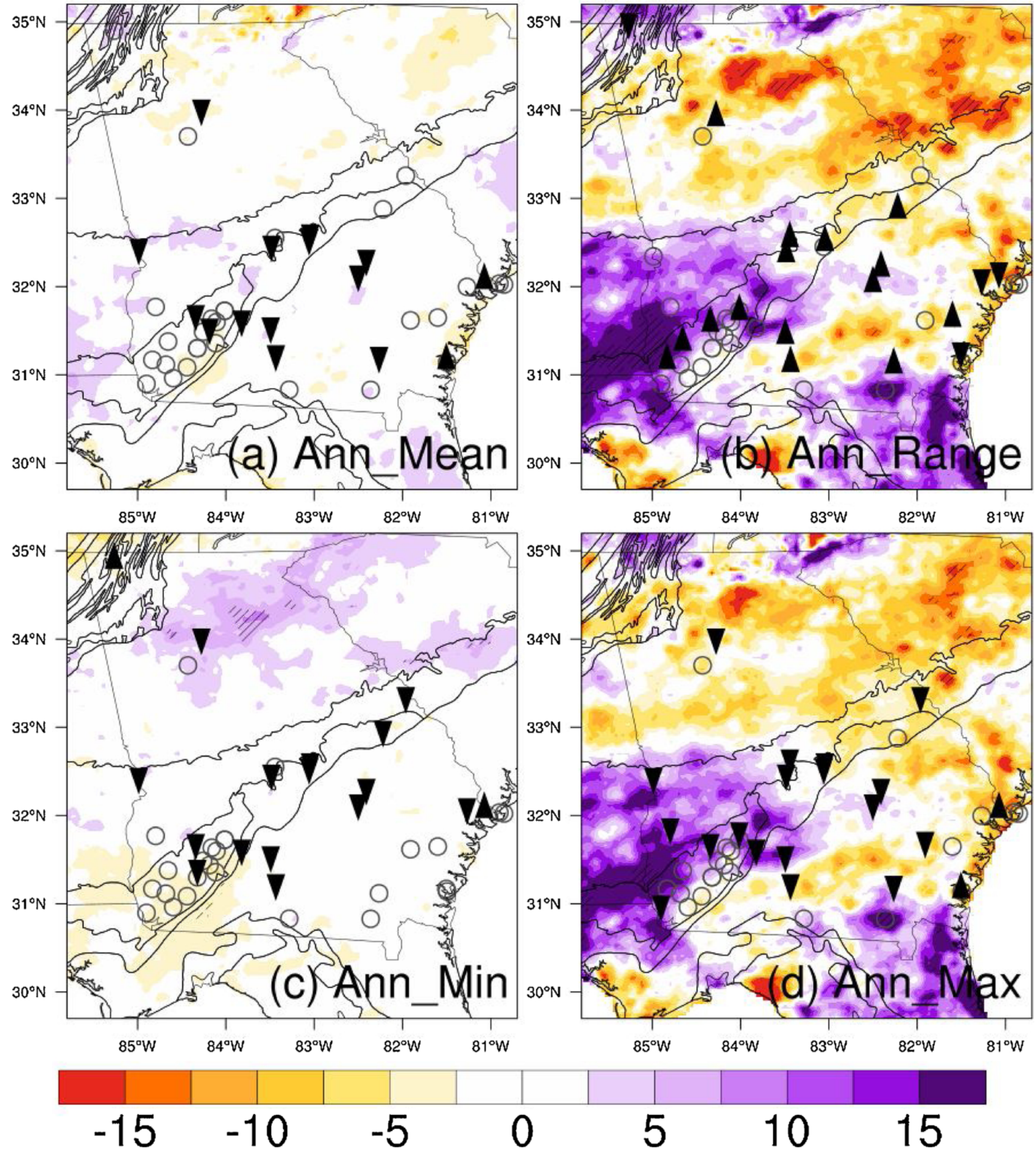

Fig. 3. Trends in groundwater and precipitation from 1981 to 2017. The groundwater trends are shown by the up arrow for a statistically significant increasing trend, down arrow for the decreasing trend, and open circles for no trend. The statistical significance is calculated under LTP consideration (see text) and at a 95 % confidence level. Color contour shows the precipitation trend (unit: mm per month per decade) using monthly PRISM precipitation data, and the statistical significance is shown by hatching. (a) Ann_Mean: Annual average, (b) Ann_Range: the difference between the 1-day maximum and 1-day minimum, (c) Ann_Min: Annual 1-day minimum, and (d) Ann_Max: Annual 1-day maximum time series.

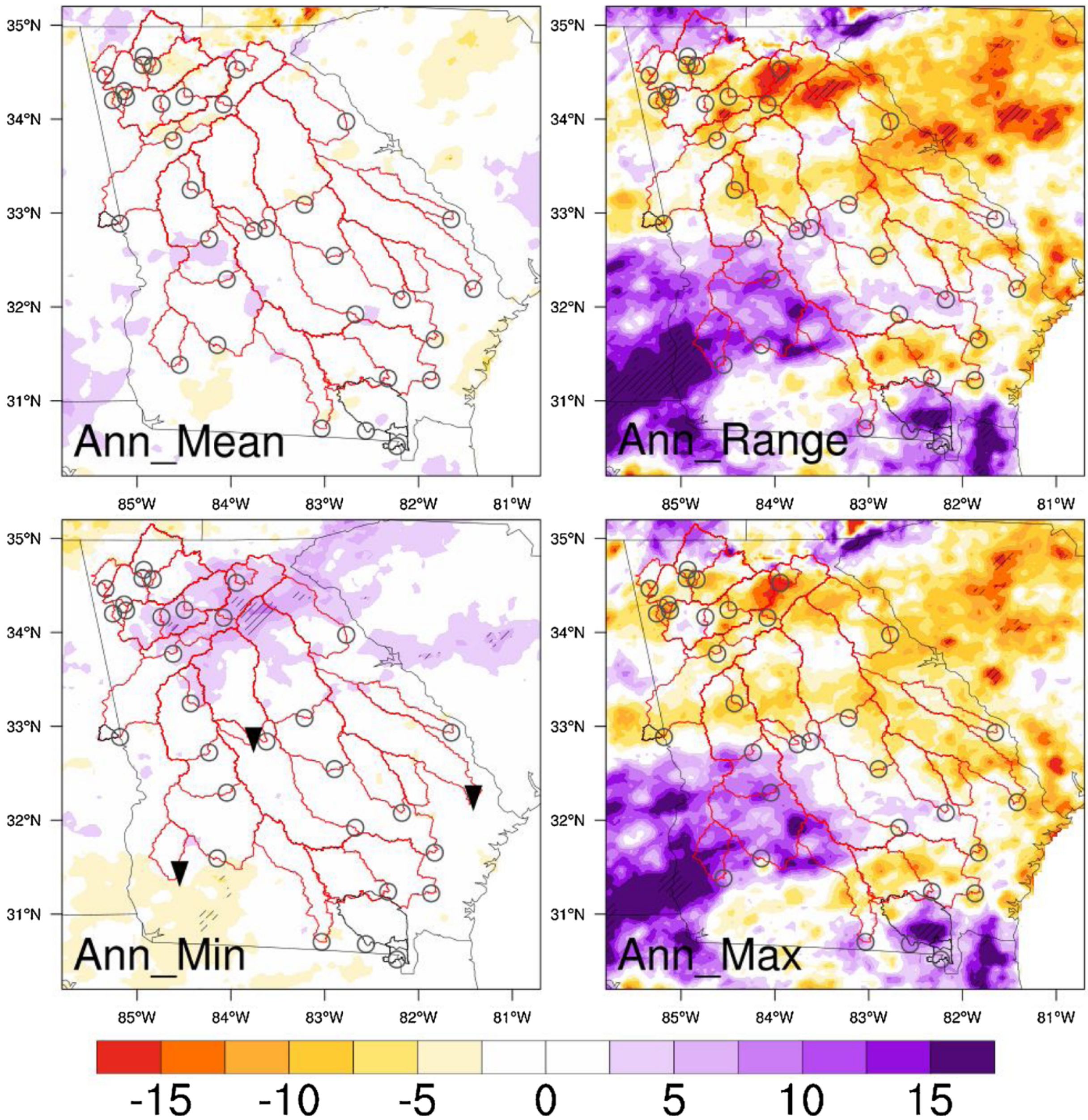

Fig. 4. Same as Fig. 3 for the streamflow (surface water).

statistically significant long-term precipitation trend over the last 65 years (Fig. 1b). Most irrigation expansion has occurred over the southern half of Georgia, where productive aquifer systems are found (Fanning and Trent, 2009; Miller, 1986). Thus, the geology and the underlying aquifer systems have played an essential role in determining the spatial extent of the irrigation expansion in Georgia (Fig. 1c–d). Most groundwater extraction is contributed to irrigation for crops in Georgia (Painter, 2019).

3.2. *Groundwater trends in Georgia*

The groundwater trends are overwhelmingly negative for annual average, 1-day minimum, and 1-day maximum statistics. As much as 30 % (13 out of 43) of monitoring wells show significantly declining annual average trends under LTP consideration (Fig. 3 and Table 1). The number of monitoring wells showing declining trends is 42 % for the annual minimum (18 out of 43), and 37 % for the annual maximum (16 out of 43) statistics. Most monitoring wells showing declining trends are in the CPAS and FAS (Table 1). Considering only STP, the number of monitoring wells showing significantly declining trends increases, e.g., 49 % of wells (21 out of 43) show the declining trends under STP considerations (Supplementary Fig. S1).

The range between 1-day maximum and 1-day minimum groundwater levels are increasing in Georgia (Fig. 3b). The annual range

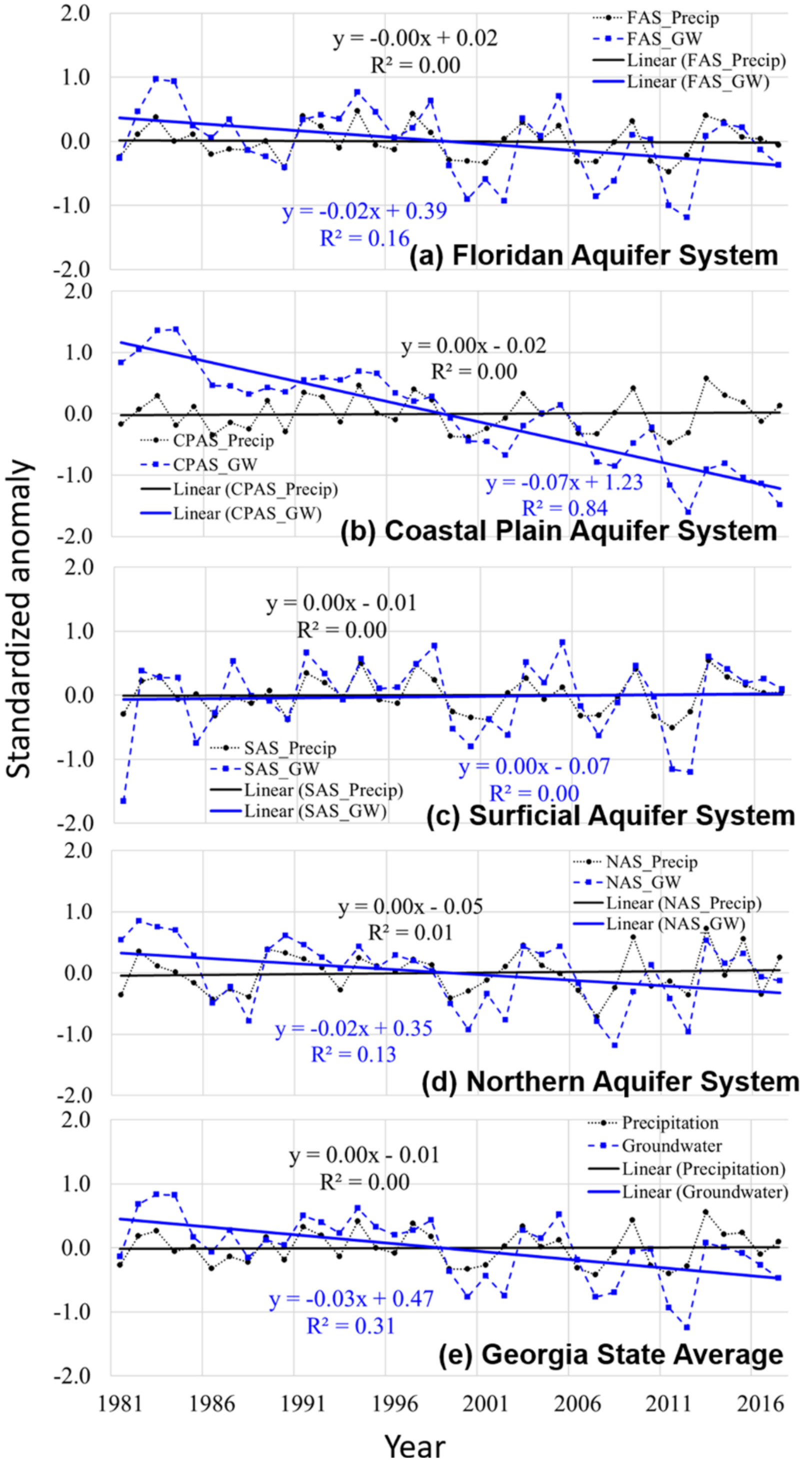

Fig. 5. The Annual average Groundwater (GW) trends and its comparison with precipitation (Precip) trends in different aquifer systems of Georgia. The linear trend line for each time series, linear equation, and R2 are included in each graph. (a) Shows the Floridan aquifer system. The Floridan aquifer system has the largest number of monitoring wells (27), so the statewide average (Fig. 5e) looks similar due to the large number of wells in the Floridan. (b) Shows the Coastal Plain aquifer system. The Coastal Plain aquifer system has the highest GW decline amongst all the aquifers. (c) Shows the surficial aquifer system. The surficial aquifer shows the least amount of change over the monitoring period. (c) Shows the Northern aquifer systems. The northern aquifer systems show large fluctuations but remain mostly neutral over the time series in terms of average water table level. (e) Shows the state average result. The precipitation data do not show a trend amongst all four aquifers.

is increasing at 35 % of stations (15 out of 43) and decreasing at 12 % (5 out of 43) of monitoring wells. The increasing annual range suggests less reliable groundwater availability (Kumar et al., 2014), which can be due to a more profound decline in the 1-day minimum than the decrease in the 1-day maximum level.

The declining groundwater trends do not correspond with the minimal or statistically insignificant trend in annual precipitation (Fig. 3). Almost the entirety of Georgia does not show statistically significant precipitation trends for all four statistics computed from monthly PRISM precipitation data (Fig. 3).

3.3. Surface-water (streamflow) trends in Georgia

Observed streamflow records show minimal or no trend which is generally consistent with the minimal trend in the precipitation (Fig. 4). Human activities impact most watersheds (30 out of 33), and therefore are categorized as non-reference watersheds (Falcone et al., 2010) (Supplementary Table 2). The USGS streamflow observations were processed using the same methodology as the groundwater data for their long-term continuous daily data availability from 1981 to 2017. Only three non-reference watersheds (9% of all watersheds) show a statistically significant declining trend in the annual 1-day minimum flow under the LTP considerations. The other flow metrics, including annual average, annual range, and annual maximum flow, do not show a significant trend. The number of stations showing a statistically significant trend in annual one-day minimum flow increases to 15 (out of which 13 show declining trends) when only STP is considered (Supplementary Fig. S2).

The streamflow trends shown in Fig. 4 are consistent with the other long-term studies. For example, e.g., Dudley et al. (2020) analyzed stormflow trends from 1966 to 2015 and found a declining trend in the 7-day minimum flow for urban-dominated watersheds in the Southeast. Singh et al. (2020) investigated long-term streamflow trends (1951–2015) in the Southeast using observations and climate modeling experiments. They found no significant streamflow trends at reference watersheds and attributed it to the vegetation growth under elevated CO_2 concentration that negatively impacts water availability in the region. Overall, we found a declining trend in the groundwater (Fig. 3), whereas the surface water (streamflow) show no trend (Fig. 4).

3.4. Drivers of the declining ground water trends in Georgia

The groundwater trends as a function of hydrogeologic characteristics, water withdrawals, and recharge variability (precipitation anomalies) are investigated here. Fig. 5 shows annual averages of standardized anomalies averaged across different wells of the four aquifer systems and the state average. We have also shown precipitation anomalies from the locations nearest to each well.

Three out of four aquifer systems show declining groundwater trends that are statistically significant (pValue < 0.05) for FAS, CPAS, and NAS under STP consideration. These three aquifer systems show long-term persistence (LTP) (Table 2). Only, CPAS shows a statistically significant declining trend after considering the LTP. The SAS shows no trend similar to the precipitation trend. The FAS largely influences the statewide average groundwater trend (Fig. 5e) due to the maximum number of monitoring wells in the aquifer (27 of the 43). The FAS is hydrologically interconnected with surface water bodies and may act either as an unconfined or a confined aquifer depending on location. Therefore, some similarity in trends between the surficial aquifer and the FAS is expected. Likewise, the FAS shows similarities with the deeper, mostly confined CPAS. A strong declining trend in the CPAS combined with a milder decline in FAS makes the statewide trend statistically significant (Table 2).

The confined CPAS shows the most substantial decline of any aquifer system in the state. To elaborate it further, we performed a correlation analysis between the groundwater anomaly and precipitation anomaly, groundwater anomaly and ENSO index, and precipitation anomaly and ENSO index considering all 37 years of data (Table 3). Overall, the surficial or shallower aquifers showed the highest correlation with precipitation and ENSO, while the deeper aquifers showed the least correlation with the ENSO and precipitation. One year lag ENSO index show slightly improved correlation with groundwater variability in all but the NAS. For example, the correlation coefficient improves from 0.40 for the concurrent ENSO and groundwater to 0.53 for lag-1 ENSO and groundwater in the FAS. Two-year lag ENSO and groundwater correlations are considerably smaller (not shown).

The groundwater shows a higher correlation with the precipitation than it did with the ENSO (Table 3). Previous studies have also found the relationship between ENSO and the surface water and shallow aquifer systems (Mitra et al., 2014; Singh et al., 2015, 2016). Additionally, this study finds that the CPAS, the deepest aquifer system, has the least correlation that is not statistically significant,

Table 2
Trends and persistence statistics of the aquifer average standardized anomalies of the groundwater variations shown Fig. 5. Table show TSA trend, Hurst coefficient (H), and trend's p-value of trend significance under STP and LTP considerations, and fractional contribution of the linear trend (R_{lin}). Unit for TSA trend is % of inter-annual standard deviation change per year. Two noteworthy points are: (a) TSA trends' magnitude is comparable with the linear regression-based trend magnitude (slope of the trend line) shown in Fig. 5, (b) effects of LTP consideration if H is found to be statistically significant, as shown by the bold italics letters. Trends' p-value less than 0.05 are considered statistically significant trend (95 % confidence level).

Statistics	FAS	CPAS	SAS	NAS	State Avg.
TSA	−2.0	−6.5	0.0	−2.0	−2.5
H	***0.62***	***0.72***	0.50	***0.71***	0.57
p-value (STP)	0.005	0.000	0.516	0.003	0.000
p-value (LTP)	0.097	0.004	0.516	0.138	0.000
R_{lin}	0.16	0.84	0.00	0.13	0.31

indicating a greater role of the human withdrawals, i.e., the linear trend. However, the correlation between precipitation and detrended time series of groundwater (X_{inter}, Eq. 5) becomes statistically significant for all aquifers including the CPAS (Table 3); suggesting that climate variability as an important driver of inter-annual groundwater water variability.

Contribution of the linear trend (R_{lin}) varies considerably across the aquifer systems (Table 2, and Fig. 5). For the state average, the linear trend accounts for 31 % of the total long-term variability. The linear trend contributes to 84 % of the total variability in the CPAS. Droughts and human withdrawals are both factors which have been shown to contribute to groundwater decline (Hughes et al., 2012; Humphrey et al., 2016). There are several drought periods in the the time series, e.g., drought-period 1980−82, 1985−89, 1998–2003, 2006−07, and 2012 which may have exacerbated the declining groundwater trends in Georgia (Painter, 2019). However, the area underlain by the FAS and CPAS has been shown to have a 2000 % increase in irrigation acreage between 1976 and 2013 (Williams et al., 2017) (Fig. 1d) and to be mainly supplied by groundwater withdrawals for agricultural and domestic use (Painter, 2019). This suggests that direct human intervention has played a larger role (R_{lin} = 84%)for declining groundwater trends in the CPAS. The irrigation has also expanded considerably in the FAS, but it shows a smaller contribution of the linear trend (16 %). Hence, we conclude that contribution of the linear trends is dependent upon the hydrogeologic characteristics of the aquifer system.

3.5. Spatial variability in trends and comparison with the remotely sensed total water storage anomalies (GRACE) data

There is considerable spatial variability in groundwater trends (Table 2, and Fig. 3), e.g. 13 out of 43 monitoring wells state-wide show significant decline in annual mean trends with LTP consideration, and 2 wells show increasing trends. Even in the CPAS, only 4 monitoring wells (out of 10) show statistically significant decline. Out of four statistics investigated here, Annual 1-day minimum (Ann_Min) shows highest number of wells (18 wells) with statistically significant decline.

To understand the spatial representativeness of the our monitoring well results (e.g. Fig. 5), we compare the state average results with the GRACE data that provides total water storage anomaly at coarse spatial resolution (~100 km) (Landerer and Swenson, 2012). The GRACE data show a very similar trend to groundwater throughout the comparative periods (2002–2016, correlation coefficient = 0.87) (Fig. 6). A strong agreement between the monitoring well data and GRACE indicates that the analysis is consistent with an independent water balance metric.

3.6. Characteristics of groundwater aquifers in Georgia

The memory time-scale (τ) was least for the surficial aquifers system, and highest for the deep aquifer system. We computed the seasonal autocorrelation function for groundwater anomalies averaged for each aquifer (Fig. 7). The unconfined SAS shows the least memory among various aquifer systems, around six months for all seasons, with a slight increase in memory in the summer season. The NAS looks relatively similar to the SAS, but with slightly longer memory in the summer and fall seasons. The FAS shows more extended memory than the previous two aquifers substantially with a memory of 12–18 months, depending on seasons. Lastly, the confined CPAS shows the most extended memory with a memory of over 24 months across all months.

The NAS and FAS show autocorrelation that approaches zero and then “reemerges” back to statistical significance. Previously, this has been shown to indicate that deeper soil layers with more memory have forced a long memory in the shallower layers (Kumar et al., 2019). Similarly, seasonally varying processes have been shown to provide long-term thermal memory in extratropical oceans (Alexander and Deser, 1995; Alexander et al., 1999; Deser et al., 2003).

The potential reemergence of groundwater appears to occur in both the FAS and NAS between 12 and 18 months. Reemergence is the strongest from late summer through winter months (JAS through DJF). The FAS has a strong correlation from the JAS season with a 17-month lead through the NDJ season with a 14-month lead. This indicates that the correlation of the JAS season groundwater table anomaly with the DJF groundwater table anomaly 17-months later (e.g., JAS 2015 anomaly correlating with DJF 2016–2017 anomaly). A similar reemergence is seen in the NAS from the MJJ season through the NDJ season.

3.7. Discussion

The groundwater trend analysis finds a declining trend especially in the confined aquifer system, e.g. CPAS. Our analysis suggests two different processes are affecting how groundwater aquifer systems are connected to climate variations in Georgia. The surficial or unconfined SAS and NAS aquifers show groundwater variability consistent with climate variability. Furthermore, the groundwater

Table 3
Correlation Analysis for Georgia groundwater (GW) anomaly with precipitation (PCP) anomaly, and ENSO anomaly. Statistically significant correlation values at 95 % confidence level are shown in ***bold italics*** letters. GW_dtrend refers to detrended timeseries of groundwater, i.e., after removing the linear trend.

Aquifer	GW(t) & PCP (t)	GW (t) & ENSO (t)	GW(t) & ENSO (t-1)	PCP (t) & ENSO (t)	PCP (t) & GW_dtrend (t)
FAS	***0.66***	***0.40***	0.53	***0.48***	***0.70***
CPAS	0.18	0.09	0.19	***0.45***	***0.44***
SAS	***0.75***	***0.47***	0.53	***0.51***	***0.74***
NAS	***0.58***	***0.37***	0.28	***0.41***	***0.66***
State Avg.	***0.58***	***0.38***	0.43	***0.50***	***0.72***

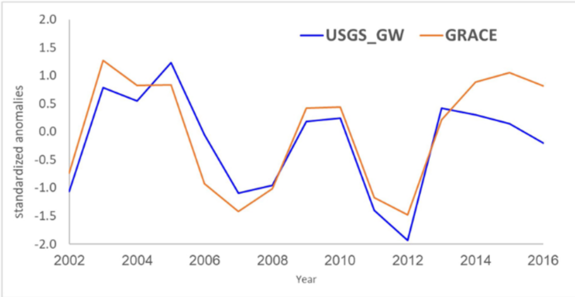

Fig. 6. Graph showing groundwater anomaly data for the statewide average USGS groundwater well data (USGS_GW) compared to GRACE data from 2002 to 2016 period. We clipped the gridded (1-degree) GRACE data to GA state boundary and computed the standardized using 2002 to 216 base period. The GRACE data and groundwater data show similar variability in the observable period (correlation coefficient = 0.87). This indicates that groundwater is fluctuating consistently with the GRACE water balance model. Because of the coarse resolution of the GRACE data, its exact comparison with the groundwater well data is not warranted.

variations in the FAS are also correlated with the precipitation and ENSO (Table 3). On the contrary, the confined aquifer CPAS has the least correlation with precipitation and ENSO (Table 3) and the most significant declining trend. After removing the linear trend, the correlation between groundwater and precipitation become statistically significant, suggesting that climate as an important driver of inter-annual variability but the linear trend may be attributed human water withdrawals.

An application of the LTP method helped us to identify secular trends in climate and water data. The number of stations showing statistically significant trend decreased considerably, e.g. from 21 stations with decreasing trend in Ann_mean groundwater under STP consideration to 13 under LTP consideration. The surface water shows minimal or no-trend under LTP consistent with the precipitation

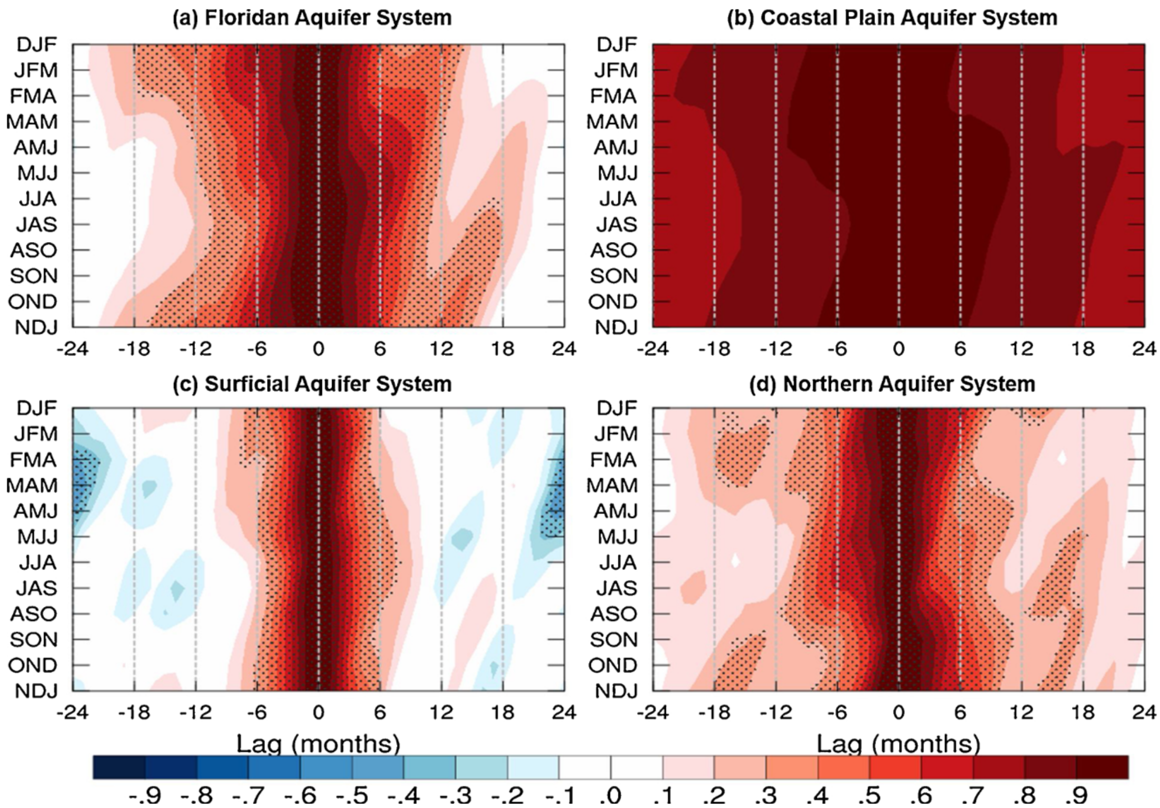

Fig. 7. Autocorrelation function of Georgia groundwater table for four aquifers. Anomalies are departures from the monthly seasonal cycle, smoothed with a 3-month running mean. Autocorrelation lag is measured from a base 3-month anomaly. For example, a lead of 6 months at NDJ represents a correlation between NDJ and the subsequent MJJ season. Plots show the annual cycle of the autocorrelation function for (a) Floridan aquifer system, (b) Coastal Plain aquifer system, (c) Surficial aquifer system, and (d) Northern aquifer systems. The vertical axis shows the time of the base season, and the horizontal axis shows the lead/lag. The statistically significant correlations at 95 % confidence are shown using stipplings in a, c, and d. All correlations in b are statistically significant, and hence stipplings were not drawn.

trend and a decrease in surface water withdrawals in Georgia (Painter, 2019). Hence, we posit that the LTP method identifies robust trends for its biophysical interpretation and attribution.

The El Nino phase (+ve ENSO) typically lead to statewide increases in the groundwater table, while the La Nina phase (-ve ENSO) typically leads to a decrease in groundwater table with the only exception being from 2013 to 2017. Groundwater table decreased consistently during the 2013–2017 period, even with a strong El Nino phase. Singh et al. (2015) found a positive correlation between ENSO and groundwater variation in the Upper Floridan aquifer in Southwest Georgia. Our new analysis shows the relationship is valid statewide not only in the Upper Floridan aquifer but also in the surficial aquifer and the northern aquifer systems. Despite the significant impacts of ENSO linked climate variability on shallow aquifers, water-level declines and storage decreases in the deeper confined aquifer are more likely caused by increased water withdrawal (Rose, 2009; Rugel et al., 2012; Seager et al., 2009; Singh et al., 2016).

The analysis of the memory time-scale confirms the association and disassociation of the groundwater variability with climate drivers. The unconfined SAS, especially, and the largely unconfined NAS to a lesser extent, share similar short memory with precipitation (~3 months, Supplementary Fig. S3). By contrast, the deeper FAS and the CPAS have a significantly longer memory than two other aquifer systems and the climatic drivers of recharge (precipitation). Significantly longer memory in the deeper, more confined aquifers show a stronger impact of human water withdrawals, e.g. 84 % of total groundwater variability is attributable to linear trends in the CPAS.

A previous study from Kumar et al. (2019) indicated that deeper soil layers with a long memory might influence the memory in the shallower layers. This study, however, lacks the data to be able to quantify a reemergence mechanism in groundwater. Potential memory reemergence of groundwater occurs in the FAS aquifer between 12 and 18 months. A possible explanation for the reemergence in the FAS could be due to the residence time of recharge from seasons of higher precipitation. The NAS is not underlain by the CPAS and varies hydrogeologically from the other three aquifers.

Most of the wells analyzed are clustered in the southern and southwestern portions of Georgia (e.g., Fig. 1b). This corresponds to the highly irrigated region. Irrigation totals in the Coastal Plains regions of Georgia have increased by roughly 2000 % since 1973 (Williams et al., 2017). Irrigation has caused the FAS to lose storage, change recharge and discharge patterns from aquifers, and cause some streams to change from gaining to losing streams (Mitra et al., 2016, 2014; Singh et al., 2016, 2017). Overall, irrigation has been shown to significantly reduce overall water storage in Georgia (Mitra et al., 2019).

Our analysis shows that all the wells, except those in the coastal region, show decreasing trends in annual average, maximum, and minimum when LTP is considered. The two coastal wells that differ from these have an overall increasing tendency (Fig. 3a). These wells have been reported to be near former municipal pumping locations, and the increase in water table may be due to ceases of pumping and / or natural recharge (GADNR, 2006).

The only metric that shows an overall increasing trend is the annual range of water table. Range measures the variation between maximum and minimum. The maximum and minimum are both decreasing, but the minimum is decreasing faster; therefore, the range between the water table high and low is increasing over time. This leads to a statewide increase in the range of the water table, indicating unreliable water availability, i.e., more energy is needed to pump the water from the deeper wells (Kumar et al., 2014).

4. Conclusions

Groundwater table elevation data from 43 groundwater USGS monitoring wells having long-term data (37 years) were analyzed for their trend to identify possible climatic and non-climatic (irrigation) drivers. Results of time series analysis indicated that groundwater levels have been decreasing on average across Georgia, and each aquifer has responded differently to climate influences. The SAS and NAS show neutral reactions across the state and correspond to changes in precipitation and ENSO, while the FAS and CPAS show moderate to severe groundwater depletion.

Mann-Kendall trend analysis shows that statistically significant water table declines mainly occur in Georgia's southern and southwestern portion with the most active irrigation (Fig. 1b). The Mann-Kendall trend analysis of precipitation and streamflow shows no significant trend, especially when LTP is considered. The FAS and CPAS show the most significant decline across most statistics tested. Previous studies have shown the FAS is affected by increasing irrigation withdrawal (Mitra et al., 2016, 2019; Mitra et al., 2014; Singh et al., 2016, 2017), leading us to conclude that the deeper CPAS is strongly affected by irrigation.

Limitation of this study include: (1) a rather short analysis period (37 years) especially when groundwater show LTP. Additionally, this study did not investigate. relationship with low-frequency climate variability mode, e.g. Pacific Decadal Oscillation which influences hydroclimate in the region (Meehl et al., 2015; Newman et al., 2016). (2) A limited geographic extent – this study was limited to Georgia, whereas the Floridan aquifer system extends southward to Florida which has experienced considerable increase in Groundwater withdrawals also (Marella, 2014). It is likely that some of the observed decline in Georgia may be attributable to the water withdrawals in the Florida. A comprehensive study that covers the full geographic extent of the aquifer system is warranted. (3) We did not incorporate water withdrawals data directly in this study which relied on available literature for irrigation expansion data (e.g., Williams et al., 2017). Incorporating water withdrawals data can further strengthen the attribution of declining groundwater trends in Georgia.

Overall, this study provides an elaborate analysis of past groundwater table trends in various Georgia aquifer systems. By incorporating streamflow and precipitation trends, this study also provides a better understanding of how climatic and anthropogenic forcing affect different aquifers at different depths and hydrogeologic conditions. Results of this study support groundwater withdrawal policy that is dependent on aquifer type, e.g. unsustainable water withdrawals from the deep confined aquifers can be disincentivized. This study provides a framework for additional research to address groundwater trends throughout the southeast USA and other regions. Addressing the factors that influence groundwater fluctuations is critical to understanding how freshwater supply could change in response to natural and anthropogenic forcing in the future.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2021.100813.

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