Effects of Climate Signals on River Discharge to Ossabaw, St. Andrew, and Cumberland Sounds

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Background

The amount and timing of freshwater delivery to estuaries have significant effects on the character and health of estuarine ecosystems. Many physical features of an estuary, such as the salinity gradient, currents, residence times of water and dissolved and particulate constituents, and sediment characteristics are affected by freshwater input patterns. These in turn help to define habitat availability for estuarine organisms. See Alber and Flory (2002) for an overview of the effects of changing freshwater inflow on Georgia estuaries.

The sources of freshwater to estuaries can be river discharge, groundwater, direct precipitation, and overland runoff. Here we focus on three estuaries in Georgia with freshwater supplied mainly by river discharge: Ossabaw Sound (Ogeechee River), St. Andrew Sound (Satilla River), and lower Cumberland Sound (St. Marys River). River discharge originates from precipitation and groundwater flow in the watershed, and can be modulated by climate processes (Royer et al. 2001; Scavia et al. 2002) as well as human activities. Thus, understanding the effects of climate on precipitation and river discharge patterns is important for understanding how freshwater delivery affects estuaries.

Large-scale climate patterns such as El Niño / Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO) and the Atlantic Multidecadal Oscillation (AMO) affect weather patterns over large areas of Earth. These climate signals (and others) are known to affect precipitation and river discharge over the continental USA (Tootle et al. 2005). ENSO warm phases (El Niño) are usually associated with increased winter rainfall over the southeast and Gulf of Mexico coasts whereas cold phases (La Niña) are usually associated with decreased winter rainfall in those areas (Ropelewski and Halpert 1986, 1996). Positive periods of the NAO are often linked to increases in the flow of warm, moist air from the tropics into the southeastern USA (Hurrell and Dickson 2004; Durkee et al. 2007). Correlations between the AMO and rainfall are weakly positive in the northeast, eastern Gulf of Mexico, and northwest coasts, stronger in Florida, and negative across much of the western and central USA (Enfield et al. 2001).

In a previous study, Sheldon and Burd (in press) investigated the effects of seven climate signals on the precipitation and river discharge patterns of the Altamaha River watershed, which provides most of the freshwater to Altamaha Sound and to the lower portions of the Georgia Coastal Ecosystems LTER site. They found that the position of the Bermuda High was associated with most of the late spring-early fall precipitation variability (after the mean annual cycle was accounted for), the ENSO cycle was associated with late fall and winter variability, and the Atlantic Multidecadal Oscillation (AMO) was associated with a long-term seasonal modulation. Two other Pacific Basin climate signals, the Pacific Decadal Oscillation (PDO) and the Pacific/North American Pattern (PNA), showed connections with Altamaha watershed precipitation and river discharge that looked like weak echoes of the ENSO connections. They found no connections with the central Pacific El Niño Modoki or the North Atlantic Oscillation (NAO).

The goal of this study was to investigate which, if any, large-scale climate drivers affect the watershed precipitation and discharge patterns of the Ogeechee, Satilla, and St. Marys rivers using the same methods as for the Altamaha River. Patterns found within these four neighboring watersheds can reveal details of the effects of climate within the southeastern US region. In addition, the estuaries fed by these rivers are sampled by Georgia DNR CRD for population monitoring of important fisheries species, and the results of this analysis will be used in a follow-up study to evaluate patterns in these populations.

Methods

The methods used in this study are the same as in Sheldon and Burd (in press) and are repeated here only in brief, with slight differences noted.

Length and Treatment of Time Series

Choosing data for this type of analysis involves tradeoffs between length of time series and having enough stations with concurrent measurements to establish spatial patterns. In the Altamaha analysis, we were able to use time series up to 100 years long with good coverage across the watershed, and we used data through 2007. Fewer stations and fewer observations were available for the watersheds examined here. We used a 54-year time period (December 1956 – May 2010) because comparable data were available across all three watersheds and each watershed had enough stations to establish spatial patterns.

We analyzed monthly time series because climate indices are generally computed on that time scale. In order to eliminate analytical problems due to autocorrelation (the correlation of time series elements with earlier values in the series), we first removed seasonal cycles by normalizing each time series month-by-month (e.g., January observations were normalized using the long-term mean and standard deviation for January). If any series still contained autocorrelation, we fit an autoregressive moving average (ARMA) model and used the residuals for subsequent analyses. The model terms needed to reduce autocorrelation are described along with each variable, below, as AR(months)MA(months). The best ARMA model structure for each climate signal remained the same as in Sheldon and Burd (in press) despite the different time period used here.

River Discharge

Mean daily discharge recorded at U.S. Geological Survey (USGS) stations at the lower end of each watershed (green dots in Fig. 1) were aggregated to mean daily discharge per month in order to ameliorate the effects of months of different lengths.

For the Ogeechee watershed, we used USGS station 02202500 (Eden, GA), which gauges 59% of the watershed above head of tide. An AR(1) model removed autocorrelation. For the Satilla watershed, we used station 02228000 (Atkinson, GA), which gauges 81% of the watershed, and an AR(1)MA(1) model.

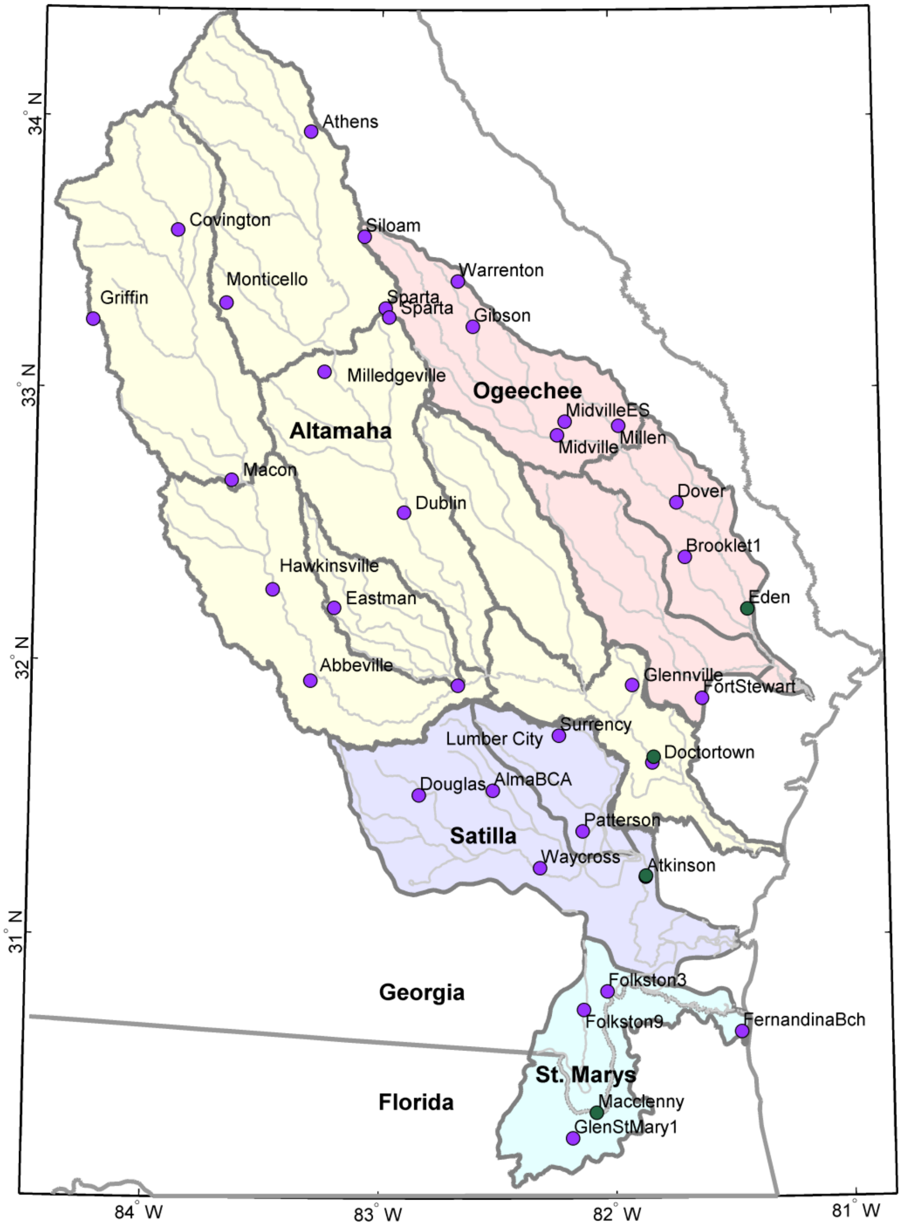


Figure 1. Ogeechee, Altamaha, Satilla, and St. Marys watersheds, showing streams and subwatersheds (gray lines). Purple dots are locations of Global Historical Climatology Network (GHCN) precipitation stations. Green dots are locations of USGS discharge gauges.

For the St. Marys watershed, we used station 02231000 (Macclenny, FL), which gauges 52% of the watershed, and an AR(1)MA(1) model.

Precipitation Stations

Daily precipitation data for all Global Historical Climatology Network (GHCN) stations (purple dots in Fig. 1) in the Ogeechee and Satilla/St. Marys hydrologic units (HUCs 030602 and 030702) were obtained from the National Climatic Data Center (NCDC). Coastal HUCs (03060204, 03070203, 03070205) were excluded because they are not in the watersheds above the main streamflow gauges. Data were aggregated to mean daily discharge per month in order to ameliorate the effects of months of different lengths.

In order to construct the longest possible time series for analysis, data from nearby stations were sometimes combined. We evaluated the potential for combining data from two or more stations using distance between stations and the coefficient of determination for any period when the series overlapped. We combined series if all of the following were true: 1) One (secondary) series had data that could fill gaps in a longer (primary) series; 2) the stations were <10 km apart (25 km was used as the cut-off in the Altamaha analysis but these are smaller watersheds); and 3) the coefficient of determination (R^2) for a period of overlap was greater than 0.8. R^2 in relation to station pair proximity is generally lower in these three watersheds than it was in the Altamaha, so few stations could be combined and in some cases we relaxed these rules slightly in order to have enough data for the analysis (described below). For non-overlapping series, we combined series if they met the proximity criterion and had similar correlations with another nearby station that overlapped both series in question, indicating that neither candidate series was unusual for the region. Secondary station data were used without modification to fill gaps in primary series if the 95% confidence limits of the slope of the primary station vs. secondary station regression included the value 1 and the intercept limits included or were very close to 0. If the slope confidence limits did not include the value 1 but the other criteria were favorable, then the regression equation was used to transform the secondary data to fill gaps in the primary series.

In the Ogeechee watershed, ten stations had sufficient data within our chosen time period to include in our analyses: Siloam, Sparta, Warrenton, Gibson, Midville Experiment, Midville, Millen, Dover, Brooklet 1, and Fort Stewart (Fig. 1). The only combined series in this list was for two Fort Stewart stations that had different station ID numbers and no time overlap, but identical geographical coordinates. This was an exception to our combination rules, as it seems to be a single location that was given two ID numbers. The southwest half of the watershed is not well represented.

In the Satilla watershed, six stations had sufficient data within our chosen time period to include in our analyses: Douglas, Alma Bacon Co. Airport, Surrency, Waycross, Patterson, and Atkinson (Fig. 1). The Waycross Ware Co. Airport series was used to fill gaps in the Waycross 4 series using a regression equation (overlap R^2=0.8). Gaps in the Atkinson series were filled using the Nahunta 6 NE station (in spite of a lower R^2 (0.52) because visual overlap was excellent except for a few outliers) and the Nahunta 3 station (no overlap, but excellent agreement with a third nearby station). The extreme northwest and southeast ends of the watershed are not well represented.

In the St. Marys watershed, no stations could be combined and only four stations had sufficient data during our time period: Glen St. Mary 1, Folkston 9, Folkston 3, and Fernandina Beach (Fig. 1). This covers the length of the watershed fairly well, but the analysis was severely limited by having only four stations with which to establish spatial patterns.

After any compatible series were combined, some gaps remained. As in the Altamaha analysis, gaps were filled using the long-term mean precipitation for that station for the missing month, modified by an anomaly value that was fit by stepwise regression using data from the other stations to take advantage of spatial correlations. Most gaps were 7 months or less, as in the Altamaha analysis, but three stations in the Satilla each had one longer gap: Surrency (36 months), Waycross (30), and Patterson (36). Not filling these longer gaps would have resulted in rejection of the stations and too little data to analyze, so we filled these gaps as well as the shorter ones.

The data for each station were deseasonalized and linear trends with respect to time were removed. No stations showed residual autocorrelation.

Climate Signals

We examined the relationships among watershed precipitation, river discharge, and four climate signals: El Niño/Southern Oscillation, North Atlantic Oscillation, Bermuda High position, and Atlantic Multidecadal Oscillation. These were chosen either because they explained variability in Altamaha watershed precipitation or because they have been shown to be important elsewhere in the southeastern US. We did not evaluate Pacific Basin signals that were shown to be unimportant in the Altamaha River watershed analysis (El Niño Modoki, Pacific Decadal Oscillation, Pacific/North American Pattern).

El Niño / Southern Oscillation (ENSO/SOI)

The Southern Oscillation is the atmospheric counterpart to the patterns in eastern tropical Pacific Ocean sea surface temperature known as El Niño (warm phases) and La Niña (cool phases). Collectively, this coupled ocean-atmosphere pattern is known as ENSO. The Southern Oscillation Index (SOI) is based on the difference in sea level pressure anomalies between Tahiti and Darwin, Australia. We used raw monthly pressure data from the Australian Bureau of Meteorology, normalized the pressure difference by month when constructing the SOI, and removed autocorrelation using an AR(1)MA(1) model. Despite normalizing over a different time period, differences in index values from the Altamaha analysis were extremely small (mean absolute difference = 0.0186, maximum absolute difference = 0.1022).

North Atlantic Oscillation (NAO)

The North Atlantic Oscillation (NAO) describes north-south fluctuations in air pressure differences between the higher and central latitudes of the North Atlantic Ocean. We used monthly station-based (Azores – Iceland) index data from the National Center for Atmospheric Research (NCAR). An MA(1) model was used to remove autocorrelation. Recent values were added to the series used in the Altamaha analysis but older values had not changed.

Bermuda High Index (BHI)

While the northern pole of the NAO generally remains in the vicinity of Iceland and Greenland, the southern pole moves east-west and is variously known as the Bermuda High or the Azores High depending on position. This oscillation is characterized by the Bermuda High Index (BHI), which is a relative index of the approximate position of the western edge of this high pressure area. We constructed the BHI as the monthly normalized pressure difference between Bermuda and New Orleans using NCAR station data (Katz et al. 2003). An MA(1) model was used to remove autocorrelation. Despite normalizing over a different time period, differences in index values from the Altamaha analysis were small (mean absolute difference = 0.0439, maximum absolute difference = 0.2460).

Atlantic Multidecadal Oscillation (AMO)

The Atlantic Multidecadal Oscillation (AMO) is a long-term oscillation in North Atlantic Ocean sea surface temperatures. We used monthly unsmoothed index values from the U.S. NOAA ESRL Physical

Sciences Division. Their website notes that the index has been recomputed and supersedes earlier datasets, so we updated our entire time series. Relative to that used in the Altamaha analysis, early values (1856 – 1937) are now higher and later values (1950 – present) are now lower. The major multidecadal pattern remains the same. An AR(1) model was used to remove autocorrelation.

EOF Analysis and Correlations

We used empirical orthogonal function (EOF) analysis to find the common spatio-temporal patterns within the precipitation time series (Sheldon and Burd, in press). EOF analysis decomposes the dataset into mutually uncorrelated modes each consisting of a spatial pattern (referred to here as the EOF) and a time series (referred to here as the principal component (PC)) (Wilks 2011). EOF 1 and PC 1 describe the pattern that explains the most variability in the dataset, with successive EOFs and PCs explaining additional variability through different patterns in the data.

The principal components of precipitation were compared with monthly standardized anomalies of river discharges and climate indices. Since lags are expected from climate drivers to precipitation to river discharge, variables were cross-correlated month by month (e.g. January precipitation with ENSO signal in each prior month for a year) in order to detect partial-year correlations and changing lag times. The de-correlated series (ARMA model residuals) were used to detect connections between variables, as this should minimize spurious correlations. However, the autocorrelations within the series (e.g., the months-long evolution of an ENSO event) are real phenomena that serve to spread effects over several months. Therefore, once a connection was found, the autocorrelated series were used to gauge the actual length of events such as precipitation following an ENSO event. Correlations are shown if they are significant at $p<0.05$ and have $r^2 > 0.01$. Correlations are characterized using the Cohen scale where $0.1 < |r| < 0.3$ denotes weak, $0.3 < |r| < 0.5$ denotes moderate, and $|r| > 0.5$ denotes strong correlations.

Results

Watershed Precipitation Patterns

The Altamaha analysis, with 7-13 stations depending on time range, identified three EOFs as showing significant patterns rather than noise (Sheldon and Burd, in press). The Ogeechee analysis with 10 stations identified two significant EOFs, and the Satilla and St. Marys with 6 and 4 stations, respectively, identified one significant EOF. The difference in the number of significant EOFs between studies most likely reflects the smaller amount of data rather than a lack of patterns, and it hampers comparison across all four watersheds. EOF patterns (whether statistically significant or not) were nevertheless very similar across all watersheds, considering the more limited data in the smaller ones. EOF 1, accounting for about two-thirds of the variance, is nearly spatially uniform across each watershed (Fig. 2). It indicates that precipitation varies mostly in unison across each watershed at the monthly scale, according to the value of PC 1. EOF 2 (which explains about 10% of the variance in the Ogeechee and Altamaha watersheds) has a spatial pattern that alternates NW-SE along the long axes of the watersheds (Fig. 2). It represents a seesaw modulation of precipitation patterns up- and down-watershed, with more rain in the lower watersheds and less in the upper watersheds when PC 2 is positive and the opposite pattern when PC 2 is negative. EOF 3, which was only significant in the Altamaha watershed (Fig. 2), explains about 5% of the variance and has a spatial pattern that radiates from the southwest side near Macon. It represents a cross-watershed modulation in precipitation patterns.

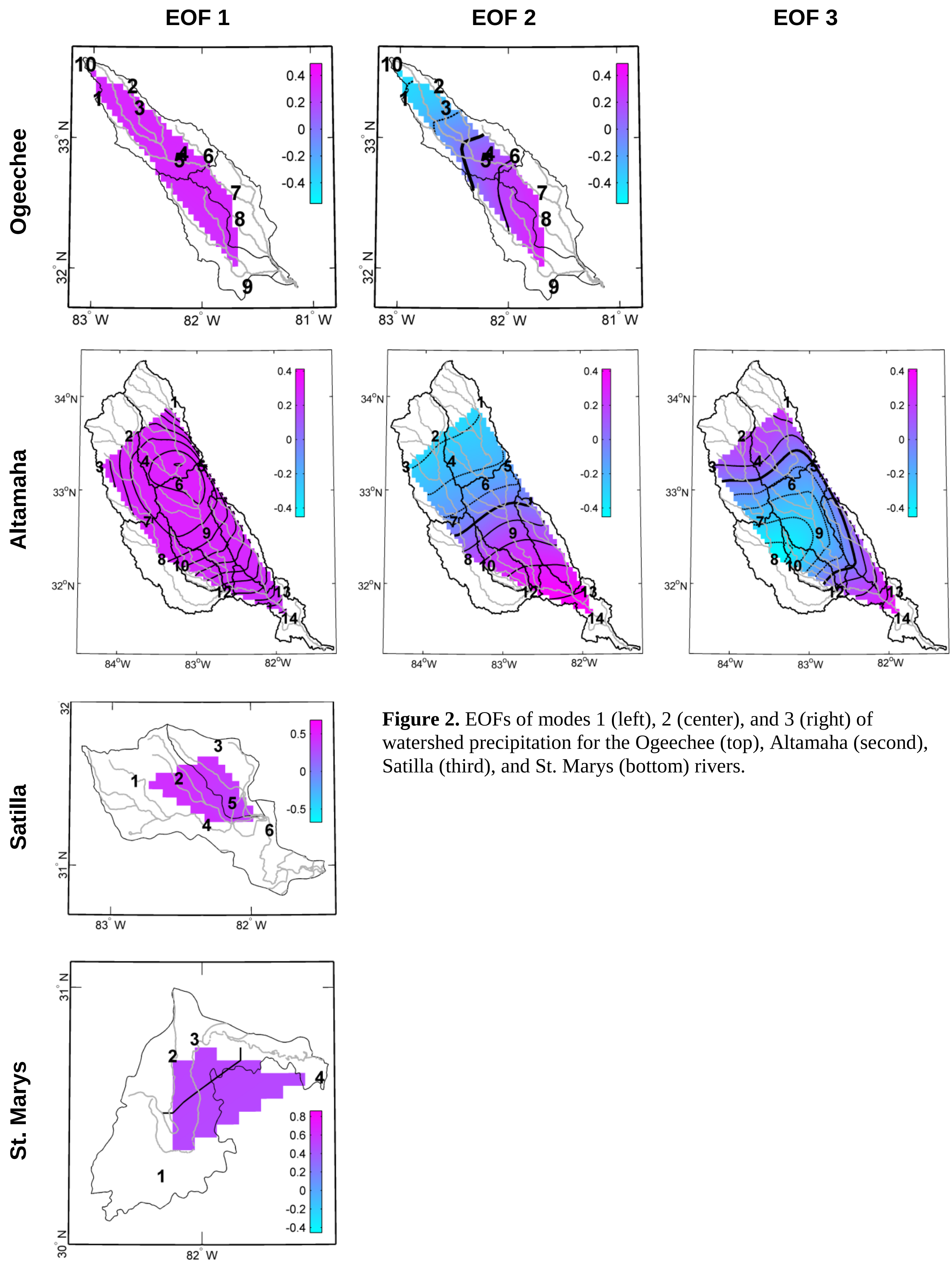


Figure 2. EOFs of modes 1 (left), 2 (center), and 3 (right) of watershed precipitation for the Ogeechee (top), Altamaha (second), Satilla (third), and St. Marys (bottom) rivers.

Correlations with River Discharge

In the Altamaha, we found that mean watershed precipitation was strongly correlated with river discharge at the Doctortown gauge (r=0.52) with a 1-month lag. When river discharge was compared to the individual PCs of precipitation, it was moderate-strongly correlated with PC 1 at 0- and 1-month lags during all months of the year, weakly correlated with PC 2 (no lag) in February and December, and weak-moderately correlated with PC 3 (1-2-month lags) in June, July, November, and December (Sheldon and Burd, in press).

Using the raw gap-filled data, mean Ogeechee watershed precipitation was moderately correlated with river discharge at the Eden gauge (r=0.39) with a 1-month lag. River discharge was moderate-strongly correlated with PC 1 at 0- and 1-month lags during all months of the year except September, and in most months discharge and PC 1 also correlated at a 2-month lag. In addition, river discharge was moderately correlated with PC 2 at 2- to 7-month lags in July and September.

Mean Satilla watershed precipitation was moderately correlated with river discharge at the Atkinson gauge (r=0.40) with no lag. Discharge was moderate-strongly correlated with PC 1 at 0- and 1-month lags during all months of the year, and in most months the two were also correlated at a 2-month lag.

Mean St. Marys watershed precipitation was moderately correlated with river discharge at the Macclenny gauge (r=0.50) with no lag. Discharge was moderate-strongly correlated with PC 1 at 0- and 1-month lags during all months of the year, and at longer lags in a few months.

Correlations with Climate Signals

Linear correlations (Pearson r) between climate indices and other variables were mostly weak to moderate. In Figure 3, each square represents the significant ($p<0.05$) correlations involving climate signals in a given month and a precipitation PC or river discharge in a given month. The squares on the diagonal represent a 0-month lag, and the x-axes are extended to a second year to accommodate longer lags. Within each square, correlations with up to three climate signals are represented within triangles as shown in the legend. Darker colors indicate stronger correlations. Non-uniform lags provided the highest correlations, indicating seasonal variability in the timing and strength of the associations. Low-frequency signals tend to produce correlation patterns in which multiple months of the climate signal are correlated with a given month of the precipitation or river discharge series (evident as vertical patterns in Fig. 3).

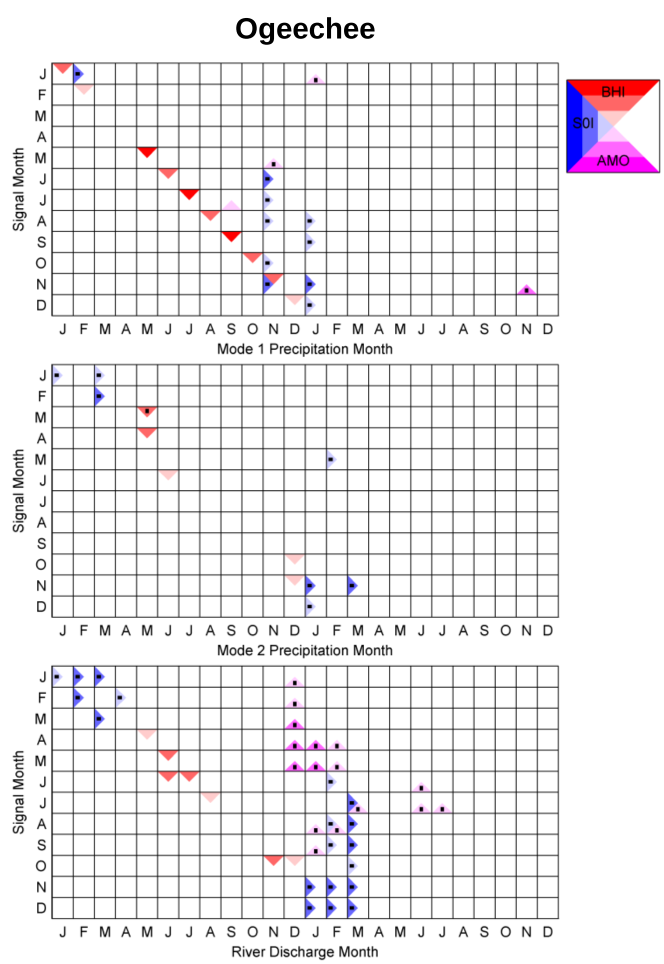
The correlation patterns reported here for the Ogeechee, Satilla, and St. Marys watersheds strongly resembled those found for the Altamaha watershed (Sheldon and Burd, in press). The results of the current analyses are summarized below, but see Sheldon and Burd for further discussion of the literature regarding these climate signals in the southeastern U.S.

Bermuda High Index (BHI)

Correlations between BHI and precipitation are generally positive because an eastward position of the Bermuda High (positive sign convention) allows storms to enter the region. The BHI was moderate/strongly correlated with the precipitation PC 1 time series in each watershed from late spring through fall (with no lag) and with river discharge lagged approximately 1 month (red triangles on a diagonal in Fig. 3). This indicates that the Bermuda High has a large, direct effect of routing storms to or around this region during summer and fall.

El Niño / Southern Oscillation (ENSO/SOI)

Correlations between SOI and precipitation are generally negative because of the sign convention of the SOI (negative for El Niño). SOI in summer-winter was weakly to moderately correlated with the precipitation PC 1 time series in each watershed in the following fall-winter (blue triangles with strong vertical patterns in Fig. 3). In the Ogeechee and Altamaha watersheds, the fall-winter SOI was also moderately correlated with precipitation PC 2 in winter. In the Satilla and St. Marys watersheds, PC 1 correlations were stronger but combine aspects of PC 1 and PC 2 correlations in the other watersheds. This may be an artifact of having less data and not being able to distinguish a second pattern clearly. SOI correlations with river discharge resemble those with precipitation, with additional lags of about 1 month. ENSO effects take a few months to reach this region, are primarily a fall-winter phenomenon, and show some different effects even within a single watershed (EOF 1 vs. EOF 2).



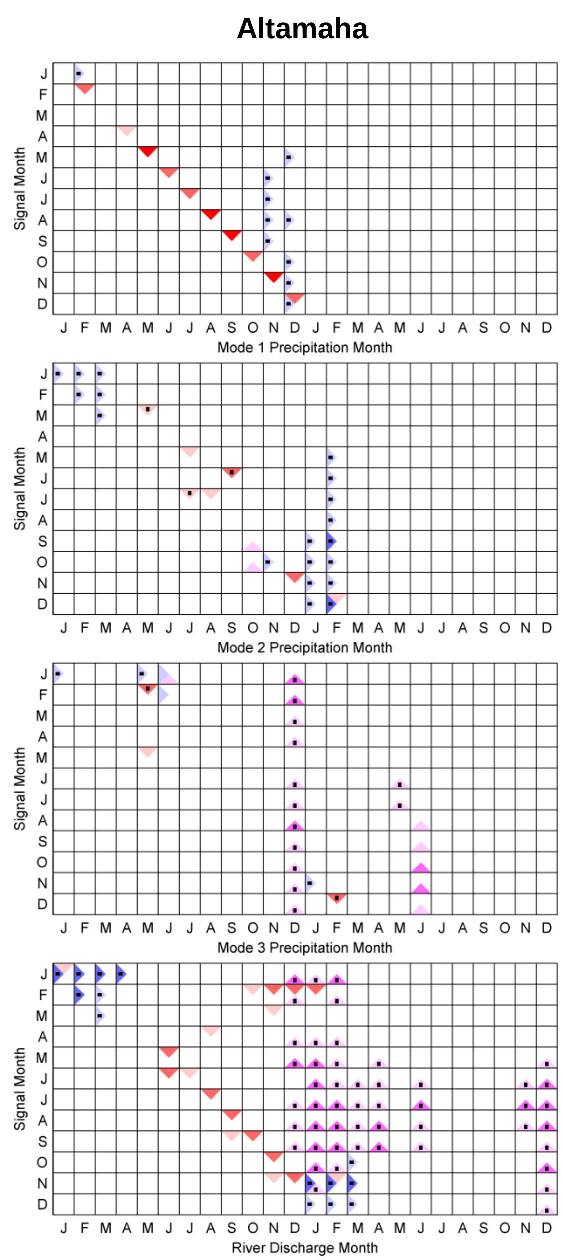


Figure 3a. Monthwise correlations between climate signals and the principal components from an EOF analysis of Ogeechee (left) and Altamaha (right) watershed precipitation and river discharge. In each square, the left triangle is the SOI, the top is the BHI, and the bottom is the AMO. The intensity of the triangle color denotes the strength of the correlation (weak: 0.1 < |r| < 0.3, moderate: 0.3 < |r| < 0.5, strong: |r| > 0.5), and negative correlations are indicated by a dot within the triangle

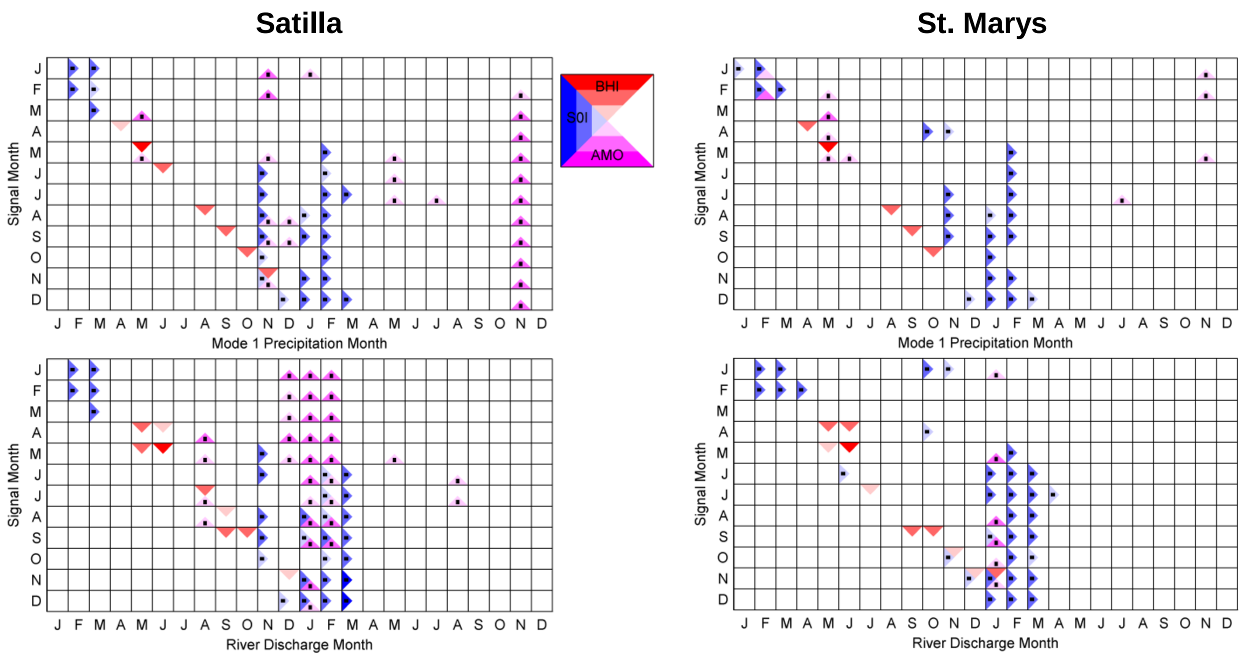


Figure 3b. Monthwise correlations between climate signals and the principal components from an EOF analysis of Satilla (left) and St. Marys (right) watershed precipitation and river discharge. In each square, the left triangle is the SOI, the top is the BHI, and the bottom is the AMO. The intensity of the triangle color denotes the strength of the correlation (weak: $0.1 < |r| < 0.3$, moderate: $0.3 < |r| < 0.5$, strong: $|r| > 0.5$), and negative correlations are indicated by a dot within the triangle

Atlantic Multidecadal Oscillation (AMO)

The overall effect of AMO in both Georgia and Florida is to alter the seasonality of freshwater delivery (Kelly and Gore 2008; Sheldon and Burd, in press). In the Altamaha watershed, where three EOFs could be considered, the AMO was most strongly correlated with precipitation PC 3 in December and June with lags up to 1 year (Sheldon and Burd, in press). This relatively minor modulation of the stronger patterns that are connected with the other climate signals tends to enhance seasonality differences in peak rainfall across the Altamaha watershed during AMO warm (positive) phases and to reduce seasonality differences during AMO cool phases. The AMO patterns are somewhat different in the three watersheds considered here. In the Ogeechee watershed, there were weak correlations with precipitation PC 1 in winter and none with PC 2, but PC 3 could not be evaluated. In the Satilla and St. Marys watersheds, where only precipitation PC 1 could be evaluated, the AMO was weakly to moderately correlated with PC 1 in early summer and early winter, with lags up to 1 year (pink triangles with some strong vertical patterns in Fig. 3). This stronger correlation with PC 1 (explaining more variability) in the more southern watersheds could be an indication of stronger AMO effects in south Georgia, or it may simply be an artifact of having less data and a smaller watershed and not being able to distinguish three EOF patterns. However, larger-scale studies support the idea that AMO effects are stronger in Florida (Enfield et al. 2001). AMO correlations with river discharge were generally stronger than those with precipitation except in the St. Marys watershed, and they were generally negative in sign (smaller discharge during AMO warm phases). River discharge may be integrating precipitation and other effects in ways that are not reflected in the precipitation analysis, especially in the watersheds with poor precipitation data coverage. The St. Marys River discharge may be problematic for this analysis because the most downstream gauge (Macclenny) is relatively far upstream of the mouth.

North Atlantic Oscillation (NAO)

As in the Altamaha watershed analysis, we investigated correlations with the NAO because it is an Atlantic Ocean signal known to affect temperature along the U.S. east coast (Rogers 1984; Hurrell and Van Loon 1997). However, we found only sporadic, inconsistently signed, and likely spurious correlations (not shown) with precipitation and river discharge in each of these watersheds.

Discussion

Given the demonstrated importance of freshwater inflow levels to establishing and affecting estuarine characteristics, it is important to understand what affects the timing and variability of freshwater inflow. The analyses presented here and in Sheldon and Burd (in press) have found statistical linkages between three climate signals and precipitation and river discharge to four Georgia estuaries. The complex, seasonally alternating pattern of climate signals that affects precipitation and river discharge in the Altamaha River watershed (Sheldon and Burd, in press) extends to the neighboring Ogeechee, Satilla, and St. Marys watersheds. Within the limitations of the data, the Bermuda High Index (BHI) and El Niño/Southern Oscillation Index (SOI) connections appear to be consistent across the Georgia coast, with Bermuda High position affecting rainfall during summer-fall and ENSO affecting it during late fall-winter. The Atlantic Multidecadal Oscillation (AMO) imposes a long-term seasonality modulation that is weaker in the Ogeechee and St. Marys watersheds than in the Altamaha and Satilla watersheds, although the apparently weak effect in the St. Marys watershed may be an artifact of having less data. We also evaluated the North Atlantic Oscillation (NAO) but found no consistent correlations in any of the watersheds. Climate-precipitation signals all propagated, to some extent, to lower watershed river discharge 0-1 month later (Fig. 3). Thus, changes in large-scale climate signals as well as the interplay among them have the potential to affect the amount and seasonality of freshwater entering these estuaries, which in turn will affect fundamental estuarine characteristics such as longitudinal salinity profiles and mixing time scales.

These long-term correlations do not establish whether any given weather event can be attributed to a climate signal, but rather address the likelihood that climate patterns will lead to one or another type of weather. Nevertheless, it is instructive to examine the climate signal patterns during recent years (Fig. 4). Since 1998, Georgia has experienced three significant droughts (1998-2002, 2006-2009, and 2010-2013) interspersed with some high rainfall events (2003, 2005, 2009-2010, and 2013). During the 1998-2002 drought, the BHI was mostly in a very negative (westward, storm-blocking) phase, but it was more neutral in 2006-2009 and neutral with a few westward migrations in 2010-2013. During all three droughts, ENSO tended to be in La Niña phases. Thus, the 1998-2002 drought began during a La Niña but may have been maintained in later years by a westward Bermuda High in spite of changes in ENSO, which shifted to neutral and then El Niño conditions in 2001-2002. The 2006-2009 and 2010-2013 droughts were associated with La Niña conditions rather than with any notable extremes in BHI. The AMO, not shown, has been in a positive phase in recent decades, which may have exacerbated the lengthy dry conditions during this time period. Brief high-flow events are more difficult to attribute to climate signals, given the inherent lags. However, the high flows occurred during neutral (2003) to El Niño (2005, 2009-2010) conditions and coincided with eastward (2003, 2005) and neutral (2009-2010) Bermuda High positions, so climate conditions tending to wet weather were present and storm blocking was probably minimal. Recent events appear to bear out the overall correlations patterns that we found over longer historical periods.

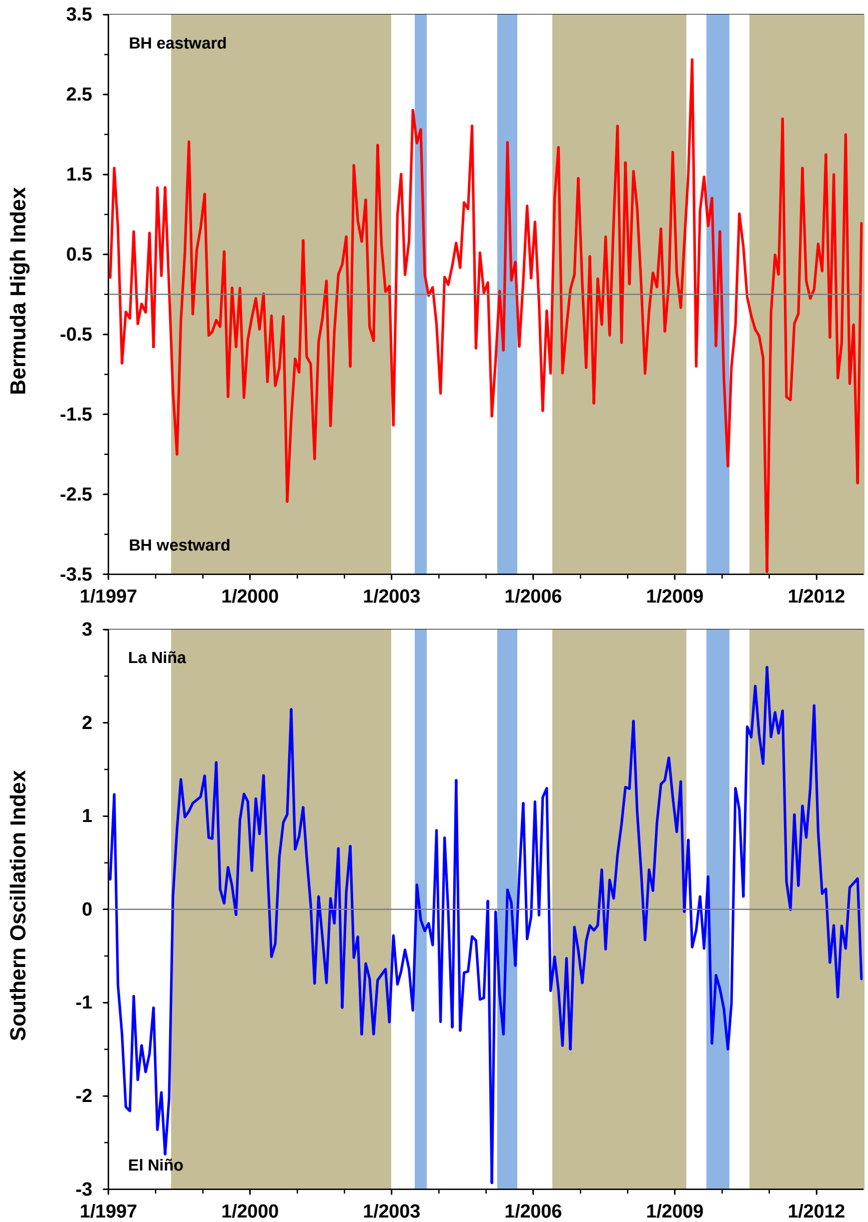


Figure 4. Values of the Bermuda High Index (top) and Southern Oscillation Index (bottom) from 1997 to 2012. Drought periods are shaded brown and high flow periods blue.

Some of the effects of the low flows and high salinities resulting from droughts on the ecology of Georgia estuaries have already been documented, including salinity-associated shifts in marsh vegetation (Higinbotham et al. 2004; White and Alber 2009) and drought-associated marsh dieback (Alber et al. 2008; Angelini and Silliman 2012). The incidence and severity of bitter crab disease (*Hematodinium perezi*) has also been linked to periods of increased salinity (Lee and Frischer 2004). The effects of the occasional high pulses of freshwater and accompanying low salinities have been less well studied. The Georgia Coastal Ecosystems Long-Term Ecological Research program, which has collected physical, chemical, and biological data on the central Georgia coast since 2000, is well-positioned to be able to address the effects of extreme changes in inflow on estuaries.

We are now in a position to move to the second phase of this project, which is to evaluate CRD's ecological monitoring trawl survey data (and the associated hydrological observations) with regard to river discharge patterns to Ossabaw, St. Andrew, and Cumberland Sounds and to interpret those findings in light of these climate connections. Such knowledge will aid in understanding the origin and extent of climatic events that may affect fisheries, such as La Niña-related droughts.

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