Modeling the Potential Impacts of Climate Change on the Water Table Level of Selected Forested Wetlands in the Southeastern United States

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Abstract. The southeastern United States hosts extensive forested wetlands, providing ecosystem services including carbon sequestration, water quality improvement, groundwater recharge, and wildlife habitat. However, these wetland ecosystems are dependent on local climate and hydrology, and therefore at risk due to climate and land use change. This study develops site-specific empirical hydrologic models for five forested wetlands with different characteristics by analyzing long-term observed meteorological and hydrological data. These wetlands represent typical cypress ponds/swamps, Carolina bays, pine flatwoods, drained pocosins, and natural bottomland hardwoods ecosystems. The validated empirical models are then applied at each wetland to predict future water table changes using climate projections from 20 General Circulation Models (GCMs) participating in the Coupled Model Inter-comparison Project 5 (CMIP5) under both the Representative Concentration Pathways (RCPs) 4.5 and 8.5 scenarios. We show that combined future changes in precipitation and potential evapotranspiration would significantly alter wetland hydrology including groundwater dynamics by the end of the 21st century. Compared to the historical period, all five wetlands are predicted to become drier over time. The mean water table depth is predicted to drop by 4 cm to 22 cm in response to the decrease in water availability (i.e., precipitation minus potential evapotranspiration) by the year 2100. Among the five examined wetlands, the depressional wetland in hot and humid Florida appears to be most vulnerable to future climate change. This study provides quantitative information on the potential magnitude of wetland hydrological response to future climate change in typical forested wetlands in the southeastern U.S.

1 Introduction

Wetlands provide ecosystem services such as groundwater recharge, water quality improvement, flood control, carbon sequestration, wildlife habitat, and recreation (*Hammack and Brown*, 2016; *Richardson*, 1994). The importance of water table level in regulating ecosystem function has long been recognized (*Sun et al.*, 2000). Water table level controls biogeochemical cycles and emissions of greenhouse gases such as CH_4, CO_2, and NO_x, and therefore have an influence on regional and global climate (*Paschalis et al.*, 2017). A small change (less than 10 cm) in wetland water table level, may have profound impacts on wetland structure and other ecosystem functions (*Webb and Leake*, 2006).

Water table level of wetlands is strongly influenced by the variation and change in climate (*Brooks*, 2009; *Fossey and Rousseau*, 2016; *Liu and Kumar*, 2016), and continued regional wetland area losses are predicted in the United States and globally (*House et al.* 2016; *Nicholls*, 2004). Water table level of wetlands in the southeastern United States (SE US) may be particularly dynamic (Li et al., 2013; Lu et al. 2010). There are already indications of climate change in the SE US (*Li and Li*, 2015), and climate models project that temperature will increase by 2 to 10 ℃ by 2100 in this region (*Diffenbaugh and Field*, 2013). The severity and patterns of storms are changing as well, with more heavy downpours in many parts of the SE US, and more intense Atlantic hurricanes (Wang et al., 2010; Wuebbles et al., 2014).

Various hydrological models, ranging from regression models to complex distributed models, have been used to study hydrological response to climate change. For example, the physically based distributed model MIKE SHE has been applied to forested wetlands in the SE US (Dai et al., 2010; Lu et al., 2009; House et al., 2016). The hydrological regime of wetland forests on the coastal plains of South Carolina was found to be highly sensitive to annual precipitation and temperature changes (Dai et al., 2010). The water table of pine flatwoods in Florida was predicted to be 20-40 cm lower than that of a baseline scenario when precipitation decreased by 10 % or temperature increased by 2 ℃ (Lu et al., 2009).

Integrated studies on the impacts of climate change on multiple wetlands in the SE US are limited. Physically based hydrological models provide a refined understanding of hydrologic processes (Yu et al., 2015; Chen et al., 2015) and quantification of hydrologic states and fluxes (Qu and Duffy, 2007; Shen and Phanikumar, 2010). However, these models are generally data (Bhatt et al., 2014) and computation intensive (Vivoni et al., 2011), and their potential uses are often undercut by equifinality of parameters (*Beven*, 1993; *Kumar et al.*, 2013; *Pokhrel et al.*, 2008). Implementing distributed hydrologic models across multiple wetlands that cover a range of climatic, topographic, and management conditions is challenging due to the computational expense, lack of fine scale input data, and difficulty in application for multiple sites (*Grayson et al.*, 1992). Conversely, in spite of the weakness of assumption of static relationships between climate and hydrological response patterns in the future, statistical models have advantages of both high efficiency in computation and acceptable performance in modelling when applied over multiple sites. The performance of empirical models in climate change studies appears to be powerful when incorporating downscaled General Circulation Models (GCMs) outputs (*Sachindra et al.*, 2013; *Li et al., 2016*). For example, *Li et al.* (2016) used log-linear models for 21 rainfall stations and seven hydrometric stations to predict hydrological drought. Greenberg et al. (2015) developed an empirical model and demonstrated its utility for climate-change planning by forecasting the weekly hydrologic regimes from 2012 to 2060 and examining the indirect impacts of climate change on biological diversity.

In this study, five forested wetlands across a range of climatic/topographic gradients and different management conditions in the SE US were used to investigate the impact of future climate change on wetland hydrology (i.e., water table level.). Future climate data from 20 GCMs participating in the Coupled Model Inter-comparison Project 5 (CMIP5) under both Representative Concentration Pathways (RCPs) 4.5 and 8.5 scenarios were used. We hypothesized that the wetlands would become drier due to climatic warming and subsequent increases in evapotranspiration. We also hypothesized that hydrological responses would vary due to differences in baseline climate and wetland physical configurations.

The objectives of this study were to 1) construct and validate empirical models of wetland groundwater dynamics using long-term observational data in five typical southern forested wetlands; 2) forecast water table changes in the five wetlands under 40 climate change scenarios (i.e., 20 GCMs and two CO_2 emission pathways); and 3) investigate the key mechanisms driving the impacts of climate change in southern forested wetlands.

2 Methods

2.1 Study area

We selected five long-term research sites in the SE US representing five types of wetlands with different combinations of climate, topography and anthropogenic management disturbances. These research sites include (1) a Alligator River National Wildlife Refuge bottomland hardwood wetland (designated as AR) on the coast of North Carolina, (2) a drained pocosin wetland covered by pine plantation forest (LP) on the lower coastal plain of North Carolina, (3) a cypress pond wetland (wetland FL–WET) in north central Florida, (4) an upland slash pine forest (wetland FL–UP) in northern central Florida, and (5) a Carolina bay forest (SC) on the coastal plain of South Carolina (Figure 1). The wetland characteristics (e.g., climate, soil, vegetation, wetland type classification) have contrasting features (Table 1). These wetlands were selected with the following considerations. AR (*Miao*, 2013) and LP (Noormets et al., 2010; Sun et al., 2010; *Tian et al.*, 2015) are located in the lower coastal plain area of North Carolina within 62 miles of one another, representing lower coastal plain forested wetlands with similar climate and topography, but different management conditions. AR is a natural coastal bottomland hardwoods wetland with no tidal influence (*Miao et al.*, 2013), while wetland LP is intensively managed by the forest industry for timber production (*Manoli et al.*, 2016; Noormets et al., 2010; *Sun et al.*, 2010). LP is located in the outer coastal plain mixed forest province of North Carolina. The area has been artificially drained with a network of field ditches (90–100 cm deep; spacing 80–100 m) and canals dividing the watershed into a mosaic of regularly shaped fields and blocks of fields (*Sun et al.*, 2010). FL–WET and FL–UP (*Lu*, 2006; *Lu et al.*, 2009) represent two types of ecosystems found in the same pine flatwoods landscape with the same climate, but slightly different elevation and management. FL–UP is dominated by slash pine (*Pinus elliotii*) plantation forests on relatively high elevation, while FL–WET is dominated by naturally regenerated cypress (*Taxodium distichum*) in depressional areas in pine flatwoods. The FL research site is located 33 km northeast of Gainesville in the Alachua County of north central Florida. The SC wetland was located in Bamberg County, South Carolina, representing a typical depressional wetland in the region (*Pyzoha et al.*, 2008; *Sun et al.*, 2006) The SC wetland was covered by naturally regenerated deciduous trees (i.e., water oak, willow oak) and was surrounded by deep, well-drained sand dominated by hardwood plantations and agricultural crops (*Pyzoha et al.*, 2008; *Sun et al.*, 2006).

2.2 Databases

2.2.1 Observed water table and meteorological data

The data and the collection methods used in this study are summarized in Table 2. The meteorological variables include precipitation, air temperature, wind speed, net radiation, and other canonical meteorological factors. The daylight duration data were from The United States Naval Observatory (USNO). The dataset consists of 48,826 30-min time series observations for each variable (i.e., water table and meteorological variable) for AR, 2,922 daily time series observations for LP, and 89,121 daily time series future climate data for each variable from each GCM of all five sites. The 30-min air temperature was averaged at the daily scale for estimating the potential daily evapotranspiration using Hamon's equation (*Federer and Lash*, 1978a; *Hamon*, 1963):

$$PET_H = 29.8 \times D \times \frac{e_a^*}{AT + 273.2} \qquad (1)$$

where PET_H is potential daily evapotranspiration (mm/day), D is day length (hr), and e_a^* is the saturation vapor pressure (kPa) at the daily mean air temperature (AT, ℃) calculated by the equation modified from Dingman (2015):

$$e_a{}^* = 0.611 \times \exp\left(\frac{17.3 \times AT}{AT + 237.3}\right) \qquad (2)$$

A correction coefficient (Sun et al., 2002) was used to adjust PET calculated by Hamon's equation to better represent the forest PET for the study region. The correction coefficients for North Carolina ranged from 1.0 to 1.2 (Federer and Lash, 1978b), and was 1.3 for the Florida site (Sun et al., 1998). To be consistent and reduce uncertainty of PET estimates, 1.2 was used for all five wetlands in this study.

2.2.2 Future climate change data

The daily mean climate data were derived from 20 GCMs, a product of the Multivariate Adaptive Constructed Analog (MACA) dataset (Supplementary Table S1) for two future RCPs scenarios (RCPs 4.5 and 8.5; 2006–2099). Future climate data represent intermediate and high greenhouse gas (GHG) emission scenarios considering a historical climate forcing baseline (1950–2005) (*Duan et al.*, 2016).

The GCMs dataset was statistically downscaled from the CMIP5 model resolutions to either 4- or 6- km (*Abatzoglou and Brown*, 2012) (http://maca.northwestknowledge.net/index.php). The downscaled GCMs climate dataset was determined to be a proper selection (i.e., 90 % of Perkins PDF skill score between 0.8-0.95) across the SE US by observed means and the entire distribution of observations (Keellings, 2016). We analyzed the historical and future climate conditions key to water table level, including the daily maximum near surface (2 m) temperature, daily minimum near surface (2 m) temperature, and daily precipitation from January 1, 1950, to December 31, 2099. Daily maximum and minimum air temperatures were averaged to derive daily air temperature (*Klein et al.*, 2002). Means from 20 GCMs climate dataset were used. To analyze the historical and future hydroclimatic changes for the full time scale of the GCMs simulations (i.e., 1950-2099), we selected three representative 20-yr time periods according to

IPCC Assessment Report 5 (2014). These time periods included: the end of the 20th century (1980–1999) as a baseline, future mid-21st century (2040–2059), and the end of 21st century (2080–2099). Thus both the historical run and the future run share the same bias from the same GCMs climate dataset. The five simulation scenarios include:

i. Baseline: baseline period 1980–1999;
ii. F1: RCPs 4.5 for the future period 2040–2059;
iii. F2: RCPs 4.5 for the future period 2080–2099;
iv. F3: RCPs 8.5 for the future period 2040–2059;
v. F4: RCPs 8.5 for the future period 2080–2099.

2.3 Model Development

We used a general regression model for this study by including climatic variables and water table depth 15-day prior to the modeled date that has major controls of wetland water balances. The fluctuations of water table are a result of the water balance between inputs (i.e., precipitation (P), groundwater and surface inflows) and outputs (i.e., outflow and evapotranspiration (ET). Therefore, we hypothesized that P and ET fluxes and associated meteorological variables should largely control water table fluctuations. The lagged 15-day mean water table (i.e., water table 15 days prior to the modeled date) was also considered as potential explanatory variables following similar studies for hydroregime prediction (Greenberg et al., 2015, Webb et al., 2003), urban water demand prediction (Almendarez-Hernández et al., 2016; Arbués et al., 2004; Arbues et al., 2010, Lyman, 1992), and energy-food-water interaction modeling (Liu et al., 2017; Ozturk, 2015). The adjustment's significance of minimizing heterogeneity in the traditional Ordinary Least Squares assumptions was confirmed by including the first lagged dependent variable (Lyman, 1992; Ozturk, 2015). Additionally, the variance of the dependent variable does not change by introducing a proven wide-sense stationary ($|\beta|<1$) first-order autoregressive process ($Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t$, where ε_t is a white noise process with zero mean and constant variance σ_ε^2) (Mills, 1990). Also, the selected explanatory variables are considered to be independent.

Actual water loss from wetlands (ET) is controlled by both PET and precipitation (*Sun et al.*, 2002). PET is mainly controlled by net radiation, air temperature, wind speed, and air humidity (Hargreaves and Samani, 1982). Due to data availability, this study used the air temperature-based Hamon equation to calculate PET (Hamon, 1963). The Hamon's PET method has been widely used worldwide to estimate potential forest water use (Sun et al., 2002). Also, PET instead of air temperature was introduced into the model since PET was affected not only by air temperature but also day length, which can better reflect variation in evaporative demand in different locations compared to air temperature alone.

The temporal scale for this study is 15-days, in line with criteria used by common wetland definitions. According to the U.S. wetland regulatory standards, an area would be qualified as wetland when it is wet enough to be saturated within 1 ft (i.e., ~30 cm) of the ground surface for two weeks or more during the growing season in most years (*Tiner*, 2016). In addition, it is suggested that the water of wetlands should be held in impoundments for at least two weeks to provide weed control and also prolong wildlife use of habitat (*Nelms*, 2007). Thus, we set 15 days as the model time step, and all-time series data were transformed to 15-day intervals.

Once all possible controlling variables were examined, we used correlation analysis and stepwise regression procedures to develop a parsimonious model for predicting wetland water table dynamics for each wetland. All explanatory variables were individually standardized first and introduced to the stepwise regression procedures to select the explanatory variables that were highly correlated to the modeled water table depth. The correlation analysis between any two of the selected explanatory variables was executed to distinguish paired collinearity. To reduce the multicollinearity, each of the paired collinear variables was removed by turns, and the other selected explanatory variables were then individually reintroduced to the stepwise regression procedures to seek a balance between the best statistical performance of the model and minimal multicollinearity of the explanatory variables (*Sachindra et al.*, 2013). The correlation analysis and the stepwise regression model procedures were combined in this study to obtain an optimized model with the least number of variables and best statistical performance. Both the normality and the homoscedasticity for the five wetland sites were tested before the models were used for prediction. Also, the autocorrelation disturbance process was tested by Durbin's *h* statistic (*Bhargava et al.*, 1982). After the above tests and correlation analysis, the final model was chosen based on the coefficient of determination (R^2) and probability (P) value at a confidence level of 95 %. Data were separated into two groups that covered different periods for model development and validation (Table 2).

Limited data availability can contribute to model deficiency. Long-term, high resolution observed wetland water table data for multiple sites in the SE US are rare. For example, the Alligator River National Wildlife Refuge bottomland hardwood wetland (AR site), is located in a remote location and water table data are the only measurements that characterize the local hydrological condition. Fortunately, the dataset covered both dry and wet years at the selected sites and was available for model development and validation. At the FL–UP and FL-WET wetlands, the time series including wet and dry years (1993–1994) were used to develop the model, and the remaining data (1992, 1995, and 1996) were used for model validation (Figure 3). Then the model was applied to predict water table depth based on the GCMs dataset (1950-2099), including the baseline period (1980-1999) and the future periods (2040-2059, 2080-2099).

The modeled future water tables were presented at annual and 15-day scales to better understand the variabilities of long-term averages and short-term extremes on water table dynamics. The modeled 15-day lowest water table data were further analyzed in two ways: 1) the percentage of time when water table level is lower than 0 cm, representing the likelihood of a wetland without surface water ponding, and 2) the percentage of time when water table level was between 0 and -30 cm, representing the likelihood of saturated soil. This 30-cm definition was based on previous studies that suggested wetland soils have a 30 cm saturated fringe and the average root depth is about 30 cm (Tiner, 2016). The 30-cm depth was also observed as the boundary 'switch' for CH_4 emission (*Moore and Knowles*, 1989), ammonification, denitrification (water table depth <30 cm) and nitrification (water table depth >30 cm) (*Hefting et al.*, 2004).

3 Results

3.1 Selected models and model performance

The stepwise regression results suggest that the following linear model form best fits the water dynamics at all five wetlands:

$$Y_{it} = \alpha_{i0} + \beta_{i1} X_{1t} + \gamma_{i1} Y_{it-1} + \varepsilon_{it} \quad (4)$$

where X_{1t} is the P-PET in mm per15 days, Y is the water table depth of wetland i (i=1, 2, 3, 4, 5) in cm at time t, and t, t-1 is the current and previous time step, respectively. The residual plots and the normal probability plot of residuals showed normality and homoscedasticity for all five specific models. Durbin's *h* statistic showed that all five wetland regressions support the autocorrelation disturbance process. The predicted water tables matched the observations consistently for all five wetlands with the determination coefficient (R^2, the proportion of the variance in predicted water table depth) values ranging from 0.69 to 0.83 (Figure 2). The statistics and parameter values for the five wetlands varied (Table 3). Among the five wetlands, β_{i1} and γ_{i1} were different but generally close, ranging from 0.11 to 0.40 and from 0.77 to 0.87, respectively (Table 3). This suggests there are some site-specific differences, but the influence of P-PET and antecedent water table at t-1 time step on the modeled water table at t time step was similar across the study sites. However, the intercepts α_{i0} did vary significantly, with a maximum of 23.2 (FL–UP) and a minimum of -1.2 (AR), indicating that there may be other site specific factors that could vary across different wetlands but that are not explicitly included in the model as explanatory variables.

The statistical models were then validated using independent subsets of water table data during the validation period (Table 2, Figure 3). The average water table was over-predicted by 1.4 cm for LP (-106.25 cm for observation, -104.85 cm for prediction, with root mean square error (RMSE) of 4.92 cm, similarly hereinafter), 0.95 cm for FL-WET (19.02 cm, 19.97 cm, with RMSE of 9.23 cm), and 1.3 cm for SC (-19.1 cm, -17.8 cm, with RMSE of 5.16 cm). Also, it was under-predicted by 2.11 cm for FL-UP (-48.97 cm, -51.08 cm, with RMSE of 5.9 cm), and 0.38 cm for AR (-4.19 cm, -4.57 cm, with RMSE of 3.71 cm). The models captured the changing water table level even during an extremely dry year (e.g. 2007-2008 at LP). For the FL-WET, the water table levels were over-predicted in the normal period while the observations and the predictions matched better during the dry year in 1993. Overall, the results show that the models performed reasonably well for all five wetlands, and could be used to predict future changes in water table level due to climate change.

3.2 Projected patterns of future air temperature, PET, and precipitation

The increase of the future mean annual air temperature under RCPs 8.5 scenario, compared to the historic 1980 to 1999 baseline, is expected to be 3.9 ℃, 4.3 ℃, 4.0 ℃, and 4.4 ℃ in the future (2080 to 2099) for AR, LP, FL, and SC, respectively (Table 4, Figure S1). The average increase from the baseline under RCPs 8.5 scenario in the five wetlands would be approximately 4 ℃, which is consistent with the U.S. climate assessment report (*Pachauri et al.*, 2014). Future annual total PET, would increase by 23 % (221 mm), 25 % (238 mm), 23 % (267 mm), and 25 % (266 mm) for AR, LP, FL, and SC, respectively, in the RCPs 8.5 scenario compared with that of the historical baseline period (Table 4). The increase in PET is expected to be smaller in the RCPs 4.5 scenario (Tables S2–S6, Figure S2).

For example, PET of wetland AR would increase by 13 % (130 mm) in the RCPs 4.5 scenario (1107 mm), while the increase is 23 % (221 mm) in the RCPs 8.5 scenario (1198 mm, Table S2).

The baseline mean annual precipitation was 1266 mm, 1275 mm, 1318 mm, 1192 mm (Tables S2-S6, Figure S3) for AR, LP, FL, and SC, respectively. The annual total precipitation under RCPs 8.5 scenario would increase the most in the wetlands LP (63 mm) and SC (60 mm) (Table 4), which is nearly two times of the increase in wetland AR (37 mm). In contrast, the annual precipitation is projected to decrease at FL by 21 mm (Table 4). Unlike air temperature and PET, the magnitudes of the precipitation changes in the future RCPs 8.5 scenario were smaller than that of the RCPs 4.5 scenario (Tables S5–S6). Specifically, the precipitation would increase by 56 mm, 68 mm, and 70 mm (Tables S2-S4) under the RCPs 4.5 scenario for wetland AR, LP and SC, respectively.

The predicted PET will increase more than precipitation, causing a decrease in P-PET for all five wetlands. Specifically, the future annual mean P-PET under RCPs 8.5 scenario would decrease by 64 % (decrease by 184 mm from the 290 mm of baseline), 56 % (decrease by 175 mm from 313 mm), 175 % (decrease by 289 mm from 165 mm), and 146 % (decrease by 207 mm from 142 mm) at AR, LP, FL, and SC, respectively (Figure 4, supplementary Tables S1–S6). The decrease in P-PET is smaller under RCPs 4.5 scenario. For example, the annual P-PET at AR would decrease by approximately 75 mm (26% of baseline) under RCPs 4.5 and 184 mm (64 % of baseline) under RCPs 8.5 (Table S2).

3.3 Future water table dynamics

3.3.1 Predicted annual water table

This modeling analysis suggests that future climate change may considerably affect water table level. The annual average water table exhibits a decreasing trend in all the five wetlands predicted by 20 GCMs under both RCP 8.5 and RCP 4.5 scenarios (Figure 5). In AR, the mean water table will decrease by 4 cm from a long term historical baseline period mean of 0 cm depth (Table S2) compared to the future RCPs 8.5 scenario. The mean annual water table would decrease by 19 cm in LP (originally -100 cm, Table S3), by 7 cm in SC (originally -16 cm, Table S4), by 17 cm (originally -73 cm, Table S5) in FL–UP and by 22 cm (originally 2 cm, Table S6) in FL–WET.

3.3.2 Predicted future 15-day water table

At the 15-day and annual scale, future water table would decline at all sites under the RCPs 4.5 and especially for the RCPs 8.5 scenarios (Figure 6). For AR, the decrease of the 15-day lowest water table would be 7 cm, from -10 cm of the historical baseline period to -17 cm under the future RCPs 8.5 scenario (Figure 6). The decrease for LP, SC, FL–UP, FL–WET would be 28 cm (from -135 cm), 14 cm (from -28 cm), 23 cm (from -101 cm), and 27 cm (from -19 cm), respectively (Figure 6).

Additionally, all the predicted 15-day water table levels were negative (i.e., water table < 0 cm) at LP, FL–UP, and SC, meaning there would be no surface water ponding in the RCPs 8.5 scenario, as well as in the baseline scenario (Table 5, Figure 6). In contrast, the wetlands AR and FL–WET show a lower probability (i.e., 40 % for FL–WET, 49 % for AR) with no surface water ponding in the baseline, but a significantly increasing probability of 62 % and 93%, respectively, in the RCPs 8.5 scenario.

Despite the fact that LP, FL–UP and SC were all predicted to have no surface water (water table < 0 cm) over the study period, the soil saturation status (water table depth still within 30 cm) varied by location (Table 5). Site LP and FL–UP would completely dry up by 2099 based on the RCPs 8.5 scenario. Wetland SC was saturated 100 % of the time during the baseline period, but the saturation period would decrease to 57 % by 2099. The wetland FL-WET would be the most sensitive of the five sites. In FL-WET, the probability would increase most in losing surface water ponding (increasing from 40% to 93 % from the baseline period to 2099) and decrease most in saturated soil (decreasing from 100% to 63 %). Notably, the wetland AR would be the only wetland that would remain 100 % saturated under all future scenarios including RCPs 8.5 scenario (Table 5, Figure 6).

4 Discussion

4.1 Difference and consistency of wetland hydrology models

The lower R^2 values (0.69) of the model in FL-UP site than the FL-WET site (0.78) might be caused by other impacts beyond the model considerations, e.g. the hydrologic interaction between the uplands and the wetlands in the Florida site. Also, the temporal scale of 15 days may better capture the hydrological changes in FL-UP rather than FL-WET due to a faster drainage system in the FL-UP site. Further, different regression coefficients of climatic and hydrologic parameters (P-PET and antecedent water table at t-1 time step) and different intercepts (Table 3) among the five wetlands indicate different major controls for each of the wetland types. For example, the model shows much lower (approximately ten times) intercepts in wetland LP (-19.55) and wetland FL–UP (-23.17), compared to wetland FL–WET (-1.36) and wetland SC (-3.79). This is reasonable, given that both wetland FL–WET and wetland SC are depression wetlands, or geographically isolated wetlands (*Tiner et al.,* 2016) (i.e., ponds within flat landscape) surrounded by uplands. Thus the wetlands would be wetter and ponded more frequently than uplands. However, site FL–UP has sandy soils and would drain faster with the artificial ditching systems and higher elevation comparing to FL-WET on a flat landscape. Hence, the much lower intercepts of site FL–UP and site LP may reflect the topographic and drainage management controls for these two wetland types.

4.2 Differing controls on future water table level in different wetlands

Although the statistical model follows a similar structure, i.e., including the same two explanatory variables in all five wetlands, and is proved to have good simulation performance overall, a closer comparison of the modelled water table levels among the five wetlands shows different climate influences. For example, the future annual water table depths under RCPs 8.5 scenario decline the most in wetland FL. For the other three sites (AR, LP, and SC), this may be due to large increase in PET. Moreover, the precipitation decreases in the wetland FL, while it increases at other sites.

Future changes in precipitation and PET are predicted to vary between AR and LP. In the RCPs 8.5 scenario, the increment of PET in LP is 8 % higher than that in AR (Table 5), and the increment of precipitation in LP is 170% higher than that of AR. However, the change in P-PET is generally similar between the two wetlands (i.e., -175 mm for LP and -184 mm for AR, Supplementary Table S2-S3). Despite the similar P-PET changes, the projected future water table depth changes in AR and LP are different. The mean water table depth of LP was predicted to decrease 19 cm compared to 4 cm, for AR from the period of 1980-1999 to 2080–2099. The differences are reflected by the different intercepts of the models, and may be due to the different management conditions in AR and LP. Wetland AR is a natural undisturbed natural bottomland hardwood swamp, while LP is highly managed pine plantation forest. LP has well-established ditches for drainage, with a flowline below the surface of water table so that the hydraulic head of drains is lower than the hydraulic head of field water table depths. The drainage outflow of site LP from the watershed is closely related to the water table depth (*Amatya et al.*, 2006). Additionally, in reality at the AR wetland, other local hydrologic drivers (not directly considered by the model, e.g., sea level rise) may increasingly slow the predicted decreasing water table depth. The sea level rise related hydrology may counter the predicted future water table decline.

Wetland type also contributes to the different water table dynamics. The water table changes differ from the baseline to the future RCPs 8.5 scenario for FL–WET and FL–UP with the different topography conditions. The more significant change in FL–WET water table depth compared to the other site differences suggests that depressional wetlands may be more sensitive to climate change compared to uplands, consistent with the results of *Lu et al.*, (2009). Thus, the different responses of future water table depth in the wetlands modeled here, with varying climatic and topographic gradients and management practices, demonstrate the necessity and importance of developing wetland-specific hydrologic models.

4.3 Implications

4.3.1 Efficient modeling of wetland water table dynamics

Compared to a lumped (e.g., DRAINMOD–FOREST, Tian et al., 2015) or distributed parameter model (e.g., MIKE SHE, Lu et al., 2009), the empirical hydrological models developed in this study is simple. However, according to the model performance and results analysis in this study (Table 2, Figures 2 and 3), our models were proved to be able to well predict different water table dynamics under a range of climatic and management conditions across the SE US region. Differences in wetland hydrological response to climate change suggest that different wetland management strategies should be developed according to individual site characteristics. For example, the differences between FL–UP and FL–WET suggest that depressional wetlands have higher sensitivity to climate change. The differences between AR and LP suggest the importance of integrating the mechanisms of water table response to sea level rise and extreme storm events.

Overall, the empirical models developed from this study performed well at the site level, and can be incorporated into landscape and larger scale biogeochemical models. For example, the empirical hydrological models can be linked with local soil respiration or regional methane emission models. Such an empirical approach should be compared to process-based hydrological models to effectively quantify the biogeochemical change under future climate.

4.3.2 Biogeochemical cycles

Previous studies report that 3 to 5 ℃ increases in temperature and 146 to 192 mm/year increases in precipitation would lead to a 175 % increase in the methane emissions (*Shindell et al.*, 2004). The carbon (C) emissions in forested wetlands could be tightly linked (e.g., a logarithmic relationship) to drought or flood periods (*Moore and Knowles*, 1989). In the costal wetland (AR) in this study, *Miao et al.*, (2013) found that 93 % of the annual average soil CO_2 efflux of 960–1103 g C m^{-2} was released in non-flooded periods. Our study suggests that the non-flooded period would increase by 13 % (from 49 % to 62 %, assuming no influence in sea level rise) in the late 21st century. This translates into a 116 to 133 g C m^{-2} CO_2 efflux increase by the end of the century for this site. Other studies suggest that gross ecosystem productivity and the available carbohydrate substrates for soil respiration would decrease with drought (*Noormets et al.*, 2008). Wetland trees may also alter the use and allocation of nutrients (e.g., N cycling) in response to the changing availability of water (Vose et al., 2016).

4.3.3 Droughts and wildfires

The projected warming and future drying trends indicate an increasing threat of drought and wildfire in the study area (*Mitchell et al.*, 2014). Plant distributions may shift due to drought (*Desantis et al.*, 2007; *Mulhouse et al.*, 2005), and trees may become increasingly susceptible to attack by pests and pathogens (*Schlesinger et al.*, 2015). A warmer and longer growing seasons corresponds to an increased possibility of droughts and occurrence of wildland fires (*Vose et al.*, 2016). Furthermore, increasingly frequent wildfire would release more carbon by biomass burning (*Westerling et al.*, 2006) and stimulate other greenhouse gas (GHG) emissions (e.g., CH_4 production) (*Medvedeff et al.*, 2015). Thus, the management challenges in restoring wetland forests and reducing greenhouse gas emissions will substantially increase.

4.3.4 Wildlife and habitat

The predicted long-term drying of some sites (e.g., FL–WET) may greatly affect the biological diversity and metapopulations of wetlands by impacting the inter-wetland movements, recruitment, recolonization, and genetic exchange of many species (*Moor et al.*, 2015; *Osland et al.*, 2013). Long-term drying could reduce the dispersion among wetlands, and increase the isolation of primarily aquatic species such as cricket frogs (*Acris gryllus sp.*), pig frogs (*Lithobates grylio*), swamp snakes (*Seminatrix pygaea*), and water fowl (Greenberg et al., 2017, *Davis et al.*, 2017; *Murphy et al.* 2016). The abundance of waterfowl was greater on impoundments than on seasonally flooded wetlands (*Connor and Gabor*, 2006). Changes in the water table depth of even less than 10 cm (predicted to decline from 7 cm to 28 cm among the studied wetlands) may have profound effects on habitat choice and species composition, and provide conditions which favor certain species or communities over those currently dominant in a given wetland (*Reddy and DeLaune*, 2008). Brent geese switch habitats within a water level span of 30 cm (*Clausen*, 2000). An equation linking decay coefficient for a specific habitat type and the water table depth was illustrated *Bouma et al.* (2014). Temperature increase of 2 ℃ (projected to be 4 ℃ in this study) in Florida would influence co-occurring mangrove and salt marsh plants (*Coldren et al.*, 2016). This supports the hypothesis that wildlife habitats are at risk due to changing water table depth across the SE US.

4.4 Uncertainty

Although the models developed in this study are efficient for simulating the historic and future water levels at multiple wetlands, the models do not account the full physical processes that govern wetland hydrological cycles. For example, an increase in atmospheric CO_2 concentration is likely to increase plant water use efficiency and thus the ET and water balance of wetlands (Brummer et al., 2012). The empirical models do not explicitly simulate lateral water loss/gain from net groundwater flow (Johnston et al., 2005) and thus may cause simulation errors for certain wet periods. Thus, there is uncertainty regarding the hydrological response to extreme events such as extreme droughts or floods. In addition, wetlands are not isolated, thus a landscape approach is needed to accurately model water table changes. Although water table dynamics are also affected by site-specific factors such as ditching/drainage, subsurface flow due to topographic differences and local landscape hydrology, they were not considered explicitly as explanatory variables in our model. For example, in the AR wetland, future water table changes will also be impacted by the local hydrological change due to sea level rise (Miao, 2013). Our main objective was to evaluate the potential impacts of climate change on water table changes as forced primarily by changes in P and PET. We assume that the effects of other local site characteristic factors are nonetheless taken into account indirectly by the coefficients (i.e., intercepts) of the models.

In addition to the uncertainty associated with hydrological model structure, there are uncertainties associated with future climate change data. The GCMs precipitation/temperature projections are inherently inaccurate for small scale studies, in spite of model bias corrections that have been implemented, and multiple models are used in this application. Compared to previous studies using hypothetical climate change data or climate data from a single GCM, our approach of assembling climate data from 20 GCMs and applying separate models to multiple wetlands represents perhaps a more robust way to project hydrological response. Hypothetical or stochastically generated climate conditions were used in most previous modeling studies (*Chen et al.*, 2016). Climate data from single GCM (*Greenberg et al.*, 2015; *Wang et al.*, 2015) have been used in wetland hydrological response modeling, but using several GCMs (*Chen et al.*, 2012; *Meinshausen et al.*, 2011) could provide a more realistic assessment. However, different GCMs and future scenarios produce very different climate projections. The differences are even greater when applied to localized areas (*Alo and Wang et al.*, 2008). Multiple and overall GCMs data may provide a better full-scale estimate of climate changes (*Hessami et al.*, 2008).

5 Conclusions

The empirical models developed in this study are able to simulate water table level dynamics for different types of wetlands across the SE US. With the antecedent water table, precipitation, and potential evapotranspiration as the main predictors of water table level, the developed models are simple but powerful tools to provide useful water table changes information under a range of climatic and management conditions. Under future climate change scenarios, the decrease in water availability is predicted to be a dominant factor for all five wetlands, resulting in a drier future (e.g., 4 cm–22 cm of water table drops) in the study region, especially for isolated wetlands (e,g., site in Florida) in late 21st century. This study confirms the hypothesis that climate change may have a significant but varying influence on water table levels of different forested wetlands in the SE US.

Our study may serve as a basis for future regional studies to understand the interaction between water table level and climate and to quantify the role of wetlands in regulating regional water and energy balances. Also, the study results have important implications not only to wetland hydrology but also wetland ecosystem management. The predicted hydrological changes have the potential to impact wetland biogeochemical cycles, fire regimes, and wildlife habitats. Further studies are needed to explore the physical mechanisms of how climate change affects wetland water table dynamics and associated ecological processes. Process-based ecohydrological models are needed to fully account for the impacts of climate change on vegetation dynamics and associated hydrological changes, and also to better understand the wetland-upland interactions, and wetlands-sea level rise interactions.

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Tables

Table 1 Characteristics of the studied wetlands.

Wetland	Coordinate	Climate (mean T and P)	Soil	Vegetation	wetland type	References
AR	35°47’ N, 75°54’ W	17 ℃ in July, 7 ℃ in Jan; 1298 mm (1971-2010)	Muck and fine sand	Black gum, swamp tupelo, bald cypress, fetterbush, bitter gallberry, red bay	Natural lower coastal plain forested wetland	(*Miao et al.*, 2013; *Moorhead and Brinson*, 1995)
LP	35°48’ N, 76°40’ W	27 ℃ in July, 7 ℃ in Jan; 1320 mm (1945-2008)	Organic and loamy sand	Hardwoods, loblolly pine from 1992	Artificially managed lower coastal plain forested wetland	(*Sun et al.*, 2010; *Tian et al.*, 2012; *Tian et al.*, 2015, *Diggs*, 2004)
FL	29°48’ N, 82°24’ W	27℃ in July, 14 ℃ in Jan; 1330 mm (1992-1996)	Organic sandy soil, impermeable blue-greenclays	Flat woods: Pond cypress, slash pine, swamp tupelo (wetland); slash pine, saw palmetto, gallberry shrubs (upland)	Cypress swamps and depression wetlands	(*Lu*, 2006; *Lu et al.*, 2009; *Sun et al.*, 1998; Sun et al., 2000)
SC	33°06’ N, 81°06’ W	27℃ in July, 13 ℃ in Jan; 1193 mm (1951-2004)	Loamy sand, deep sandy soils	Bottomland hardwood trees (water oak, willow oak, swamp tupelo)	Carolina bay	(*Pyzoha et al.*, 2008; *Sun et al.*, 2006)

Table 2 Raw data summary.

Wetlands Data types		AR	LP	SC	FL − UP	FL − WET
Observation data	Meteorological data	07/02/2009–01/01/2011	01/01/2005–12/31/2012	01/01/1997–12/31/2002	01/01/1992–12/31/1996	01/01/1992–31/12/1996
	Interval	30 min	Daily, with some data missing	Daily	Daily	Daily
	Water table data	03/19/2009–12/31/2011	01/01/2005–12/31/2012	01/01/1997–12/31/2002	01/01/1992–12/31/1996	01/01/1992–31/12/1996
	Interval	Daily	Daily	Daily	Daily	Daily
Validation data	Model development Year	2009–2010	2009–2012	1997–2000	1993–1994	1993–1994
	Validation year	2011	2005–2008	2001–2002	1992, 1995–1996	1992, 1995–1996
	Interval	15 days	15 days	15 days	15 days	15 days
Prediction data	Meteorological data	01/01/1950–12/31/2099	01/01/1950–12/31/2099	01/01/1950–12/31/2099	01/01/1950–12/31/2099	01/01/1950–12/31/2099
	Interval	30 min	30 min	30 min	30 min	30 min
References	Data collection methods	*Miao et al., 2013*	*Noormets et al., 2010; Sun et al., 2010; Tian et al., 2015*	*Sun et al., 2006*	*Lu et al. 2009; Sun et al., 2000*	*Lu et al. 2009; Sun et al., 2000*

Table 3 Results for regressions of water table for five wetlands in the southeastern United States.

wetland	α_{i0}	β_{i1}	γ_{i1}	R^2	p
AR (i=1)	-1.24	0.1137	0.7698	0.81	<0.001
LP (i=2)	-19.55	0.3750	0.8530	0.83	<0.001
FL–UP (i=3)	-23.17	0.3963	0.7206	0.69	<0.001
FL–WET (i=4)	-1.36	0.2360	0.8707	0.78	<0.001
SC (i=5)	-3.79	0.1454	0.8164	0.72	<0.001

Note: i is the number of the wetlands, i=1, 2, 3, 4, 5, t denoted the time periods, $\alpha_{i0}$is the intercept estimate, β_{in} is the coefficient estimate of the variable X_n of the i wetland, γ_{i1} is the coefficient estimate of the antecedent water table at t-1 time step of the i wetland, R^2 is the coefficient of determination, and p is the associated probability value.

Table 4 Annual changes of variables from baseline scenario to scenario RCPs 8.5 of five wetlands in the southeastern United States.

Wetland	WT changes (cm)	Baseline annual WT (cm)	P (mm)	PET (mm)	P minus PET (mm)	AT (Deg C)
AR	-4	0	37	221	-184	3.9
LP	-19	-100	63	238	-175	4.3
FL–UP	-17	-73	-21	267	-289	4.0
FL–WET	-22	2	-21	267	-289	4.0
SC	-7	-16	60	266	-207	4.3

Note: WT is water table, P is precipitation, PET is potential evapotranspiration, AT is air temperature.

Table 5 A summary of 15-day water table fluctuations in growing season under future RCPs 8.5 scenario of five wetlands in the southeastern United States

Wetlands	Lowest WT (cm)	PB of No surface water	PR85 of No surface water	PB of Saturated soil	PR85 of Saturated soil
AR	-17	49 %	62 %	100 %	100 %
LP	-164	100 %	100 %	0%	0 %
FL–UP	-124	100 %	100 %	0%	0 %
FL–WET	-46	40 %	93 %	100 %	63 %
SC	-42	100 %	100 %	100 %	57 %

Note: WT is water table, PB is the probability in baseline period, PR85 is the probability during RCPs 8.5 period (2080-2099, future scenario F4). The wetlands being ineffective to store surface water in this table was for WT<0 cm in 15 days, and the soil was considered saturated still for water table >-30 cm in 15 days during growing season.

Figures

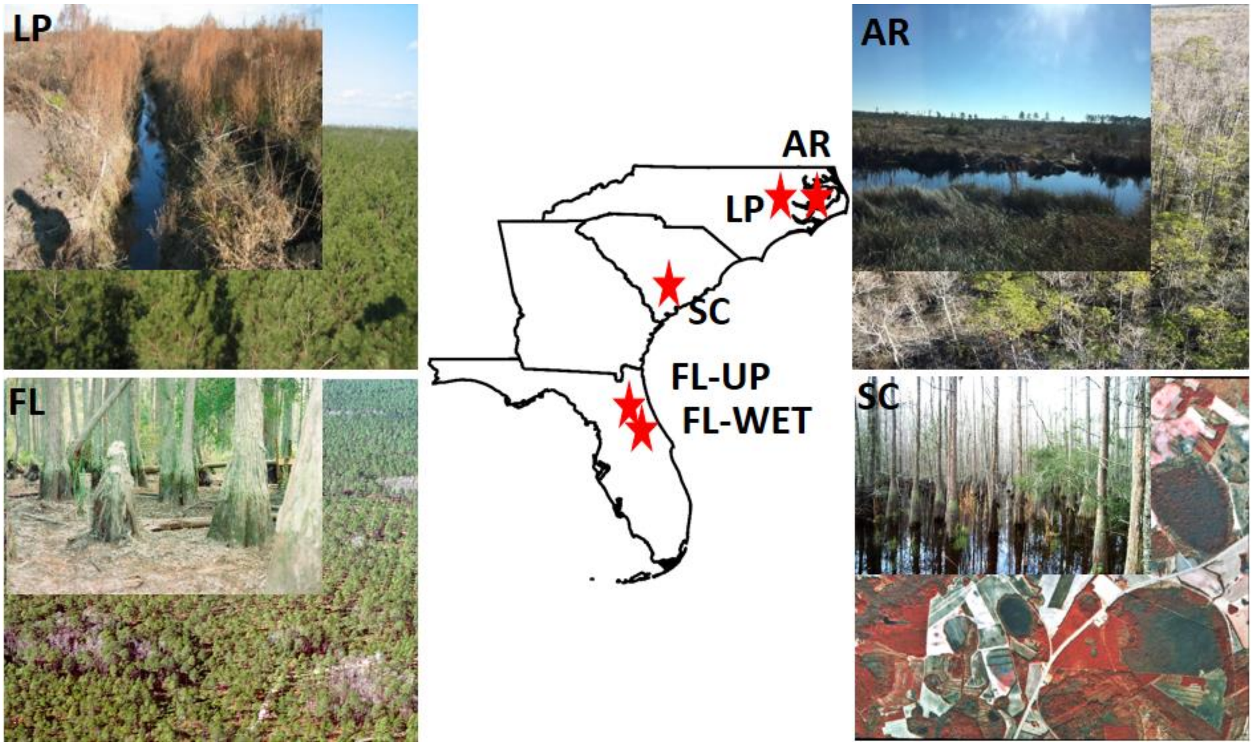

Figure 1 Study area, where the star symbol marks the study site location. Wetland AR: wetland of Alligator River National Wildlife Refuge in North Carolina; wetland LP: wetland of loblolly pine plantation in North Carolina; wetland SC: wetland in South Carolina; wetlands in Florida: wetland FL–UP (upland in Florida) and FL–WET.

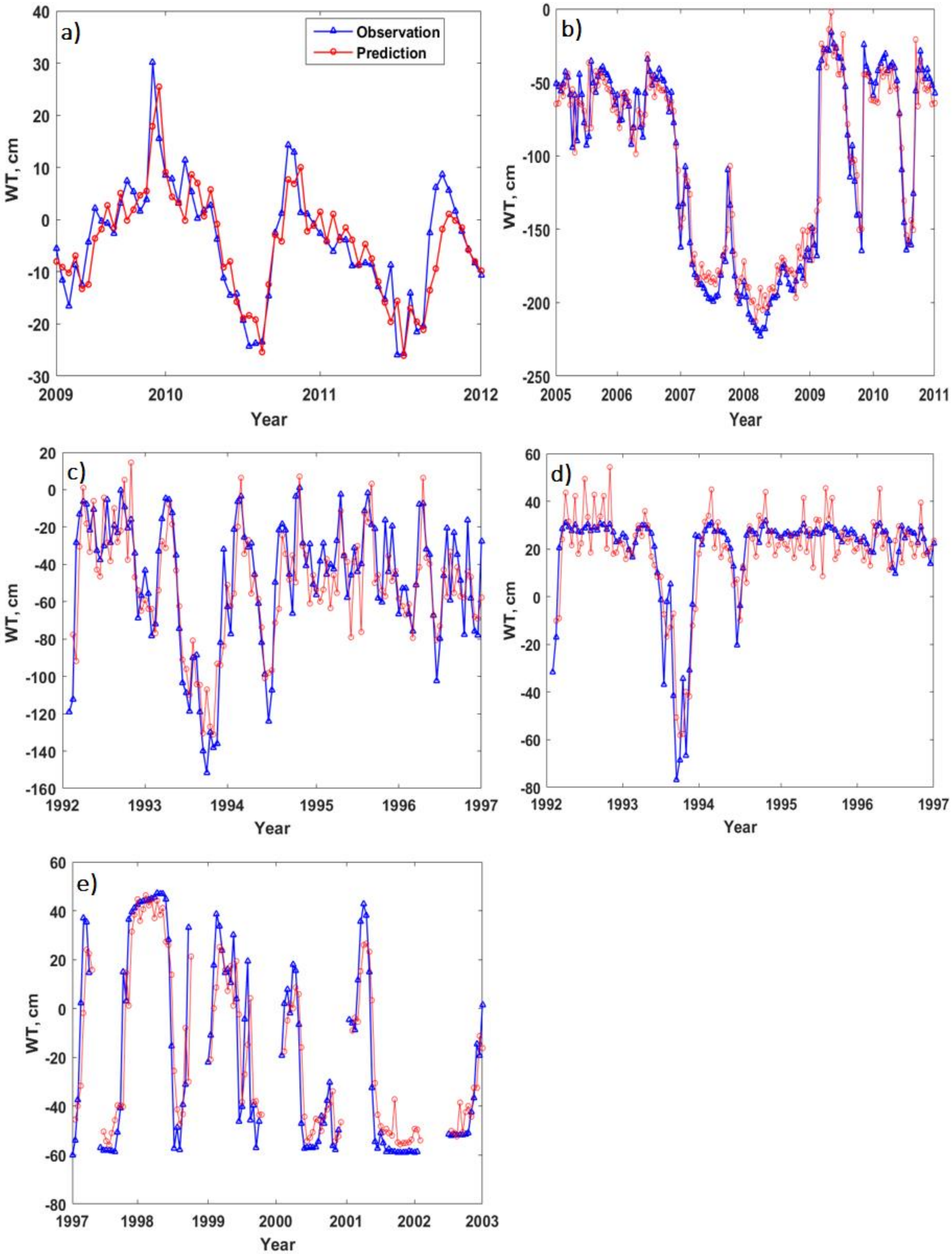

Figure 2 Comparison of observed and simulated mean water table in five wetlands in the southeastern United States, where **WT is water table, a) is site AR (Alligator River National Wildlife Refuge in North Carolina), b) is site LP (loblolly pine plantation in North Carolina), c) is site FL-UP (upland in Florida), d) is site FL-WET (wetland in Florida), e) is site SC (wetland in South Carolina).**

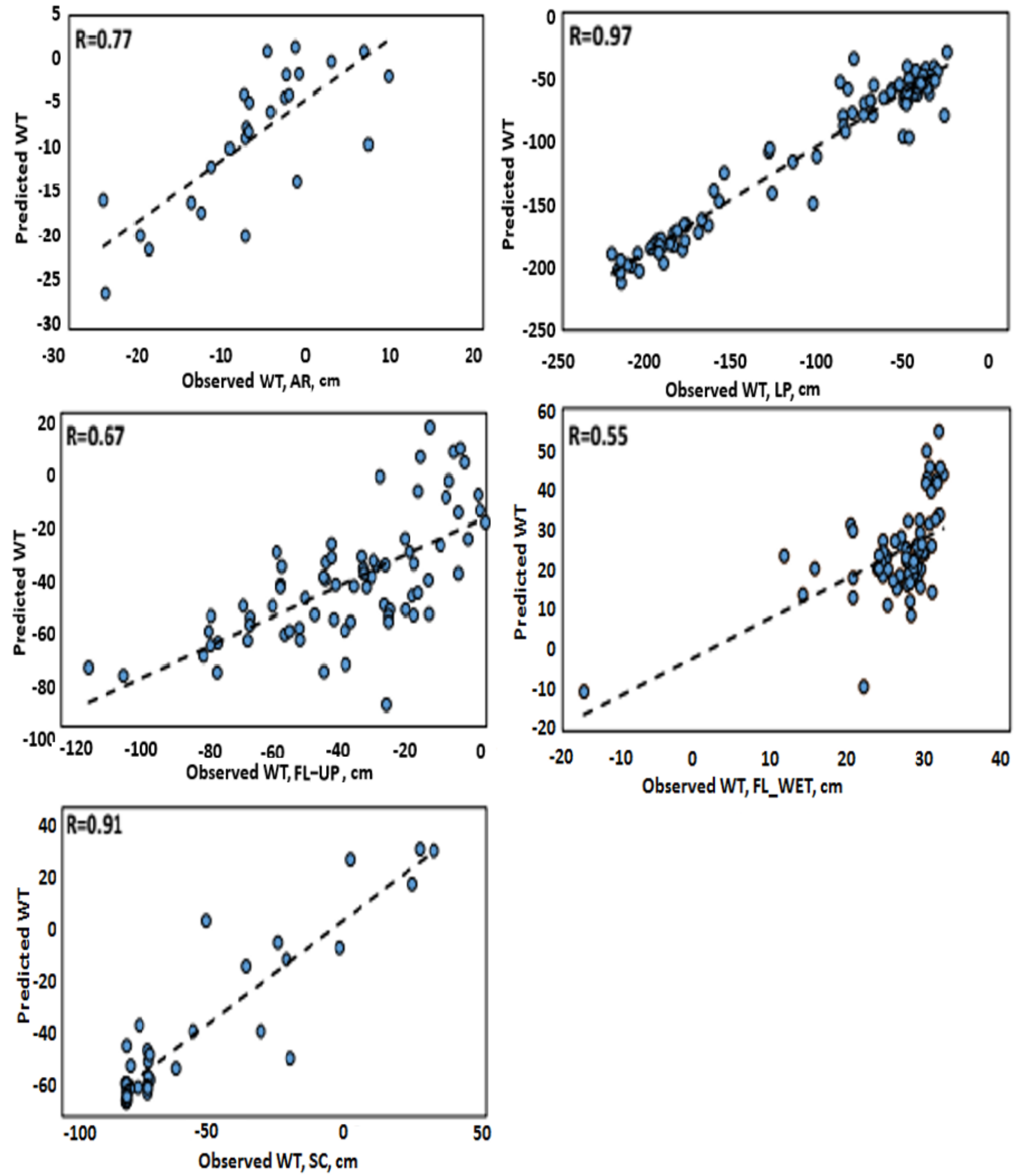

Figure 3 Scatter plots of the observed and predicted mean water table in five wetlands in the southeastern United States (unit: cm), where dashed lines are trend line, R is the correlation coefficient between observed and predicted WT.

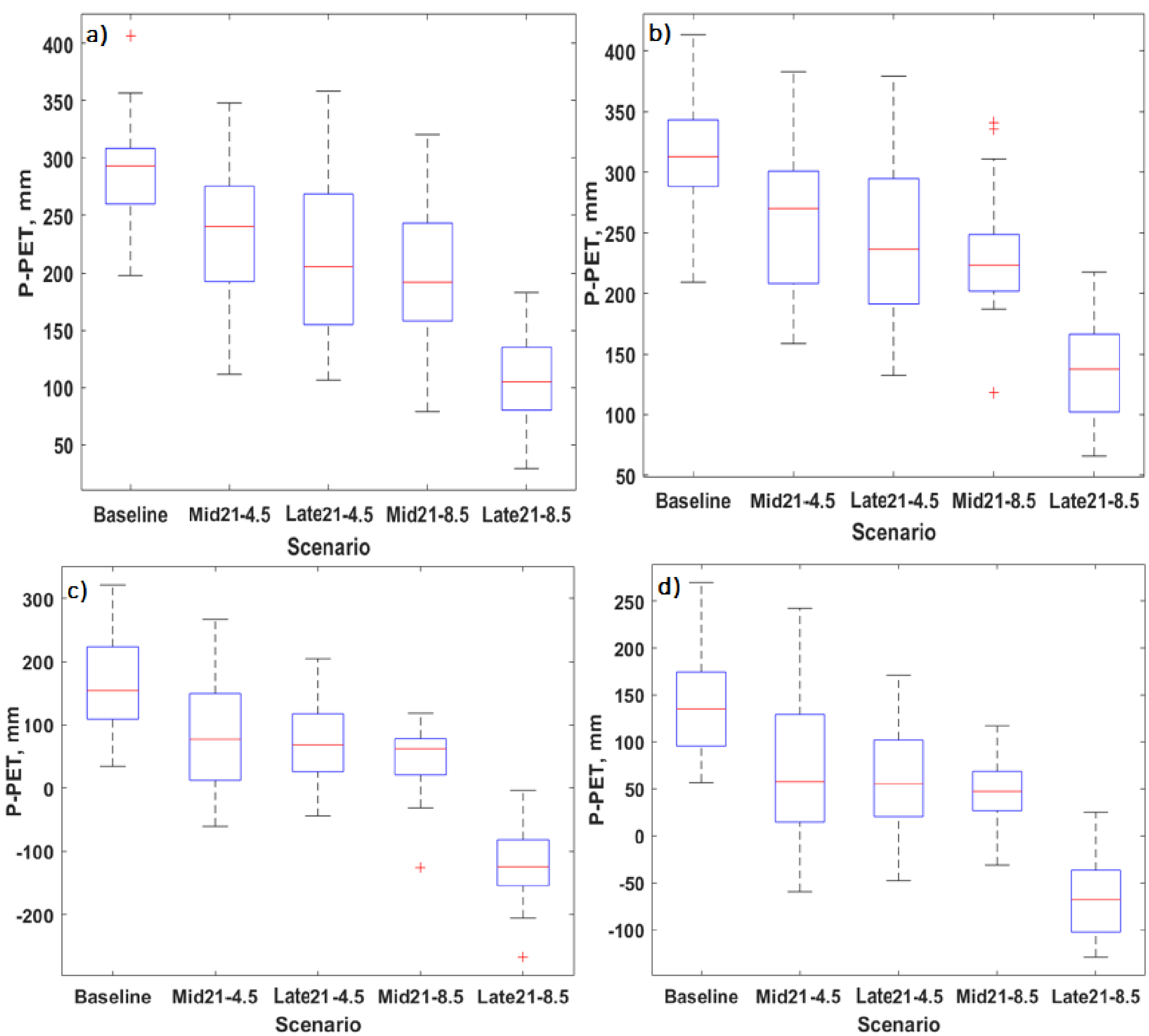

Figure 4 Total annual precipitation minus potential evapotranspiration of 20 GCMs in five wetlands in the southeastern United States (unit: mm), where a) is site AR (Alligator River National Wildlife Refuge in North Carolina), b) is site LP (loblolly pine plantation in North Carolina), c) is site FL-UP (upland in Florida), and site FL-WET (wetland in Florida), and d) is site SC (wetland in South Carolina). Baseline is 1980–1999, historical run of GCMs; mid21 is 2040–2059, under RCPs 4.5 and 8.5 scenarios; late21 is 2080–2099, under RCPs 4.5 and 8.5 scenarios.

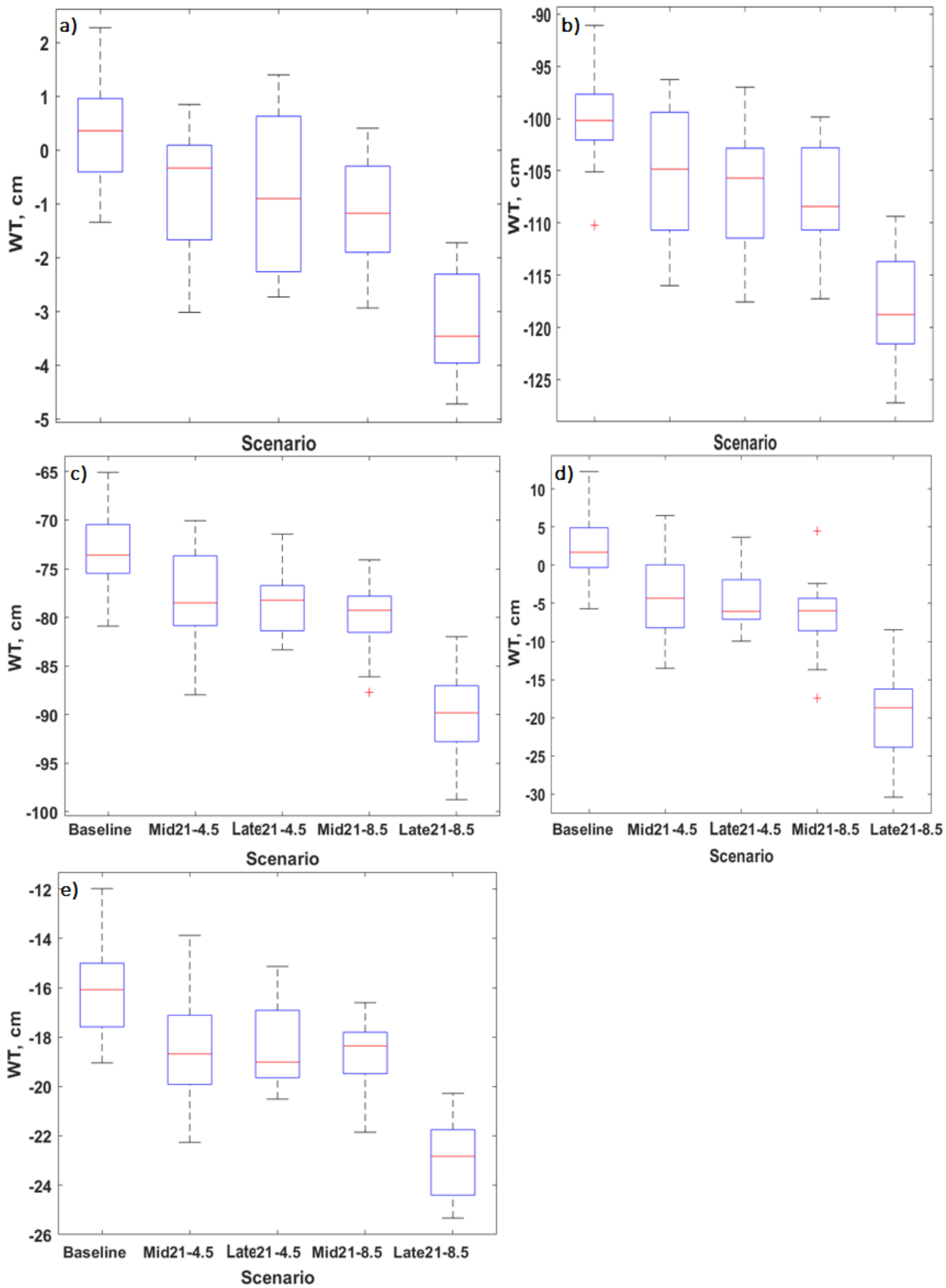

Figure 5 Mean predicted annual water table of 20 GCMs in five wetlands in the southeastern United States (unit: cm), where a) is site AR (Alligator River National Wildlife Refuge in North Carolina), b) is site LP (loblolly pine plantation in North Carolina), c) is site FL-UP (upland in Florida), d) site FL-WET (wetland in Florida), and e) is site SC (wetland in South Carolina). Baseline is 1980–1999, historical run of GCMs; mid21 is 2040–2059, under RCPs 4.5 and 8.5 scenarios; late21 is 2080–2099, under RCPs 4.5 and 8.5 scenarios.

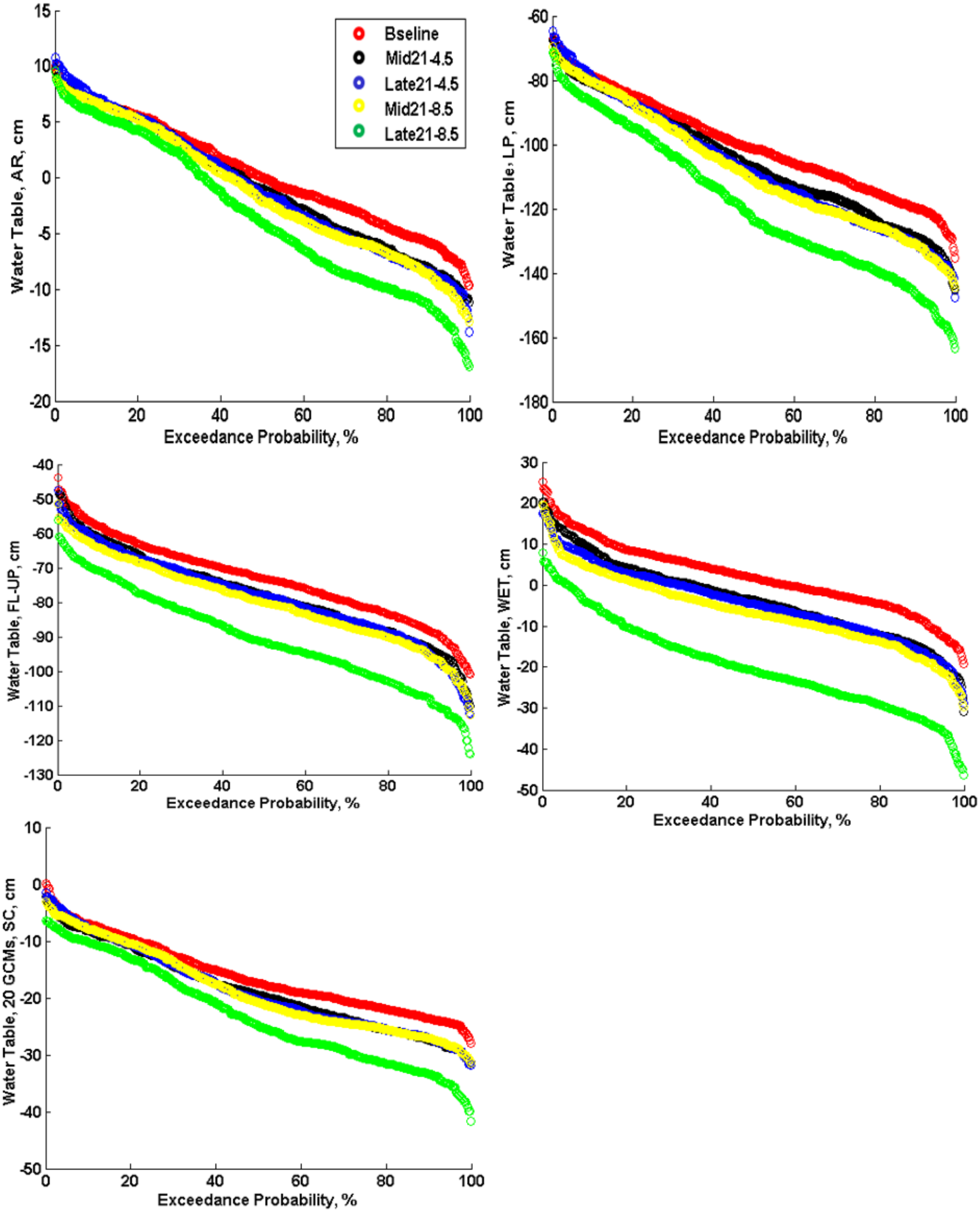

Figure 6 Exceedance probability of the mean predicted water table in the growing season of 20 GCMs in five wetlands in the southeastern United States (unit: cm) , where baseline is 1980–1999, historical run of GCMs; mid21 is 2040–2059, under RCPs 4.5 and 8.5 scenarios; late21 is 2080–2099, under RCPs 4.5 and 8.5 scenarios.