Author's Response

(1) Comments from anonymous referee #1 and author's response， Page 2-10.

(2) Comments from anonymous referee #2 and author's response， Page 11-30.

(3) Author's changes in manuscript, Page 31-63.

(4) Author's changes in supplementary materials, Page 64-71.

(1) Comments from anonymous referee #1 and author's response:

RESPONSES TO REVIEWERS' COMMENTS

We are grateful to the reviewers and associate editor for their detailed and insightful comments. In light of the suggestions, we have made efforts to significantly revise the manuscript. The suggestions and comments have substantially contributed towards improving the paper. More details are as follows:

Interactive comment on "Modeling the Potential Impacts of Climate Change on the Hydrology of Selected Forested Wetlands in the Southeastern United States" by Jie Zhu et al.

Anonymous Referee #1

Received and published: 17 May 2017

GENERAL COMMENTS: This study uses a linear regression model to estimate future water table changes in five forest sites in Southeastern US. The topic is interesting. However, this study lacks of innovation in climate change impact assessment. Besides the simple regression model, there are critical issues/errors in the methodology (see major comments). Please find my detailed comments below.

RESPONSE: This study develops site-specific empirical hydrologic models for five representative forested wetlands with different characteristics by synthesizing long-term observed meteorological and hydrological data and coupling climate changes from 20 CGMs. These wetlands represent typical Cypress Ponds/Swamps, Carolina Bays, Pine Flatwoods, and Wet Pine, and natural Bottomland Hardwoods ecosystems, and cover a range of climatic/topographic gradients and different management conditions located in the SE US. This study provides quantitative information on the different potential magnitudes of wetland hydrological responses to future climate changes for adaptive management of typical forested wetlands in the southern U.S. Based on the Reviewer's suggestions, we have added clarifications in the methodology in the revised manuscript, made relevant corrections and improvements in the title, main body, tables, figures, and also references (details see the marked version).

MAJOR COMMENTS:

Point #1

COMMENT: In fitting the regression model, water table at the current time step is the dependent variable while water table at the previous time step is included as one of the independent variables. This is not reasonable given the potential autocorrelations between current water table and antecedent water table especially at the daily scale. In fact, the unbelievably high R2 value of 0.97 in predicting water table at the LP site could be due to the inclusion of antecedent water table in the statistical model. What's more, how can future water table be predicted by the statistical model which requires inputs of antecedent water table conditions?

RESPONSE: We address reviewer's three major questions below.

(1) Reasonability of model structure using the antecedent water table as an explanatory variable,

(i) This study adopted the well-established methodology of dynamic panel model widely used in statistics and econometrics. The dynamic panel modeling includes the first lag dependent variable coupled with the explanatory variables (e.g. P, PET, in this study). The model structure with a given lag effect were successfully used in the previous 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 modelling (Liu et al., 2017; Ozturk, 2015). Lyman's (1992) and Ozturk (2015) confirmed the adjustments significance of minimizing heterogeneity in the traditional Ordinary Least Squares assumptions by including the first lagged dependent variable. Webb et al. (2003) improved the sensitivity and explanatory power of the hourly based water-air temperature regression models by incorporating a lagged response of water temperature. In a wetland hydrology and climate change study, Greenberg et al. (2015) successfully forecasting the hydroregimes of multiple wetlands by modeling the water table depth using water level of the prior week and precipitation as predictors of current water table.

(ii) The statistical model structure has physical meaning and can be viewed from the perspective of water balance. A lagged effect of water table was supported by the water balances and the water table dynamics of wetlands. It is due to the fact that wetland groundwater has memories which can be carried beyond the next season as to influence the water balance in the coming years (Miguez-Macho and Fan 2012). Firstly, the water balance of the five selected wetlands can be written as $\mathrm{WT_t} - \mathrm{WT_{t-1}} = \alpha + \beta(\mathrm{P_t} - \mathrm{ET_t}) + \varepsilon_t$. It indicates the causality balances between water tables changes (left side terms of the above equation i.e., WT_t –WT_{t-1}) and its water availability changes (right side terms of the above equation). The item of WT_{t-1} depending on the time scale can be considered as the memory effect of water tables. By moving the memory item (WT_{t-1}) to the right side, the different statistical coefficient of WT_{t-1} can reflect the different memory characters/effects in the five selected wetlands. Based on these reasons, we believe the model structure that includes a lagged water table in this study can offer more information concerning not only water tables changes due to changes in climate variables, but also the different memory effects of different wetlands in this region.

(iii) All the information is not contained in the antecedent water table conditions of wetlands. The lagged water table only offers the basis for the current condition, however, the forcings (e.g. climate and water availability in this study) alters the water table depth. In another word, the water table depth would always decrease/increase along with a given initial discharge/recharge condition for the wetland. But, a wetland actually alternatively discharges or recharges for the flatness, thus water tables fluctuated with the forcings. Therefore, both the forcings and the lagged water table would determine the water tables for a wetland. What's more, when using the water table at LP site with forcings from FL-WET site, the statistics show that in spite of the same antecedent condition, the R^2 becomes poorer to 0.54 from 0.83.

(iv) From the perspective of the proved wide-sense stationary first-order autoregressive process of water tables in the five selected wetlands, the variance will not change with the autoregressive process introduced into the statistic model. For an autoregressive process given by: $Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t$, where ε_t is a white noise process with zero mean and constant variance σ_ε^2. The first-order autoregressive process is wide-sense stationary when and only when $|\beta|<1$, because it is the output of a stable filter with a white noise input (Mills, 1990). In the wetlands analyzed in the study, the coefficient of WT_{t-1} are<1 (Table 3), indicating a wide-sense stationary autoregressive process of water table. Thus the variance of the process does not change with simulation over time, and the intertemporal effect ($\beta^n \varepsilon_1$) of shocks diminishes toward zero in the limit.

(v) From the perspective of the independence of the explanatory variables, introduce of antecedent water table does not violate the independence requirements among the explanatory variables. Independence between the explanatory variables was satisfied since correlation coefficient between P-PET and WT_{t-1} was very poor (<2.7) for the five selected wetlands in the study.

According to the comment, we added the justification in the revised manuscript (Line 161-166, similarly hereinafter) to make it clear and concise for readers.

(2) For the question of "unbelievably high R2 value of 0.97 at LP site", it was actually the correlation coefficient (R) for model verification, which was corrected in line 250-252. The model was developed with a determination coefficient (R^2, proportion of the variance in predicted water table) of 0.83, which was also the highest among the five wetlands. It appears during the verification, the model was able to well capture the variations for the entire verification period for the LP site. The good capability of LP site may be explained by the contribution of the high interception value of the statistical model, which may include the contribution of artificial drainage system of this pine plantation. As mentioned in (1)-iii, all the information is not contained in the antecedent water table conditions of LP site. The R^2 becomes poorer to 0.54 from 0.83 when using the forcings from FL-WET site, in spite of the same antecedent condition.

(3) For the question of 'daily scale', this regression model is developed at the 15-day time step, not on a daily scale (Line 174, Line 178-179).

(4) The related new references were added to the revised manuscript as follows:

"Almendarez-Hernández, M., Avilés Polanco, G., Hernández Trejo, V., Ortega-Rubio, A., and Beltrán Morales, L.: Residential Water Demand in a Mexican Biosphere Reserve: Evidence of the Effects of Perceived Price, Water, 8, 428, 2016. (Line 432-436)

Arbués, F., Barberán, R., and Villanúa, I.: Price impact on urban residential water demand: A dynamic panel data approach, Water Resour Res, 40, 2004. (Line 442-443)

Arbues, F., Garcia-Valinas, M. A., and Villanua, I.: Urban Water Demand for Service and Industrial Use: The Case of Zaragoza, Water Resour Manag, 24, 4033-4048, 2010. (Line 444-445)

Liu, G., Yang, Z., Tang, Y., and Ulgiati, S.: Spatial correlation model of economy-energy-pollution interactions: The role of river water as a link between production sites and urban areas, Renewable and Sustainable Energy Reviews, 69, 1018-1028, 2017. (Line 542-544)

Lyman, R. A.: Peak and off-peak residential water demand, Water Resour Res, 28, 2159-2167, 1992. (Line 554)

Mills, Terence C. Time Series Techniques for Economists. Cambridge University Press, 1990. (Line 568)

Ozturk, I.: Sustainability in the food-energy-water nexus: Evidence from BRICS (Brazil, the Russian Federation, India, China, and South Africa) countries, Energy, 93, 999-1010, 2015. (Line 595-596)

Webb, B., Clack, P., and Walling, D.: Water–air temperature relationships in a Devon river system and the role of flow, Hydrological processes, 17, 3069-3084, 2003. ” (Line 656-657)

Point #2

COMMENT: There are major issues related to the short calibration and validation periods for the statistical model. For example, two years of data is used for fitting regression model for the AR site while one year is used for validation. I am wondering whether climatic conditions in the validation year is significant different from the calibration year? Future climate especially for the later periods of 21st century would be quite different from the calibration periods based on which the regression model is constructed. Therefore, the historical relations trained from such a short time period may not hold in the future with significant changes in climate.

RESPONSE: We agree that regression models are limited data availability and can contribute to model deficiency (Line 195). However, long-term, high resolution observed wetland water table data for multiple sites in the southeast U.S. are extremely rare. For example, the Alligator River Wildlife Refuge bottom hardwood wetland (AR site), is located in a remote location and water table data are in the only data sets extremely valuable to characterize the local hydrological conditions. Fortunately, the dataset covered both dry and wet years at the selected sites and was ideal for model development and validation purposes. For example, at wetlands FL–UP and FL-WET, the time series including wet and dry years (1993–1994) was used to develop the model, and the remaining data (1992, 1995, and 1996) were used for model validation (Fig. 3). Additionally, the model was then applied to predict water table based on the GCMs dataset in a full time scale (1950-2099) including both the baseline period (1980-1999) and the future period (2040-2059, 2080-2099) (Line 141-151). Thus, during model applied to predict water table based on the GCMs dataset, future and historical climate will share the same bias. The changes from the historical to the future are comparable.

Point #3

COMMENT: The downscaled GCM climate should be validated for the baseline period in the study sites before it can be used for future predictions.

RESPONSE: The climate data that we used in baseline period (1980-1999) and future period (2040-2059, 2080-2099) are both the downscaled GCM climate dataset (Line 141-151). These downscaled climate datasets are found to be as a good match

(90% of Perkins PDF skill score between 0.8-0.95) regionally over the southeastern United States by means observations, and the entire distribution of observations (Keellings, 2016). Besides, both the baseline period and future period would share the same bias. Thus, the hydrologic and climate changes from the baseline period to the end of this century are comparable. According to the comment, we added a few sentences (Line 135-137 and Line 141-151) in the revised manuscript.

The related new reference was added in the revised manuscript as follows:
"Keellings, D.: Evaluation of downscaled CMIP5 model skill in simulating daily maximum temperature over the southeastern United States, Int J Climatol, 36, 4172-4180, 2016." (Line 529-530)

MINOR COMMENT:

Point #1

COMMENT: In Section 80, RCP stands for "Representative Concentration Pathway" rather than "Regional Concentration Pathways".

RESPONSE: Corrected in line 77. Thanks.

Point #2

COMMENT: Hamon's equation is selected for estimating PET. Justifications on this should be added.

RESPONSE: The justifications were added in line 167-170 as follows:
"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)."

The new reference was added to the revised manuscript as follows:
"Hargreaves, G. H. and Samani, Z. A.: Estimating potential evapotranspiration, Journal of the Irrigation and Drainage Division, 108, 225-230, 1982." (Line 515-516)

Point #3

COMMENT: In section 130, the estimated PET is adjusted to match "realistic" PET values for forests. What are the realistic PET values for forests?

RESPONSE: The 'realistic PET' was a typo; it should be the actual ET for the forests in this region. The sentence was re-written as "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." in line 125-128.

Point #4

COMMENT: The climate for the baseline period is based on observations or GCM simulations?

RESPONSE: We appreciate the reviewer's careful review. The climate for the baseline period 1980–1999 (historical run) was based on of the downscaled GCM datasets (1950-2099) (Line 141- 151).

Point #5

COMMENT: A table with a brief description of the GCMs should be added.

RESPONSE: A new table (Supplementary Table S1) with summary of the GCMs was added in the revised version.

Table S1 Summary of the 20 CMIP5 GCMs used in this study from the downscaled MACA dataset.

No.	Model Name	Country	Model Institution	Atmosphere Resolution (Lon x Lat)
1	bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration	2.8 deg x 2.8 deg
2	bcc-csm1-1-m	China	Beijing Climate Center, China Meteorological Administration	1.12 deg x 1.12 deg
3	BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University, China	2.8 deg x 2.8 deg
4	CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis	2.8 deg x 2.8 deg
5	CCSM4	USA	National Center of Atmospheric Research, USA	1.25 deg x 0.94 deg
6	CNRM-CM5	France	National Centre of Meteorological Research, France	1.4 deg x 1.4 deg
7	CSIRO-Mk3-6-0	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	1.8 deg x 1.8 deg
8	GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
9	GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
10	HadGEM2-ES	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg
11	HadGEM2-CC	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg
12	inmcm4	Russia	Institute for Numerical Mathematics, Russia	2.0 deg x 1.5 deg
13	IPSL-CM5A-LR	France	Institut Pierre Simon Laplace, France	3.75 deg x 1.8 deg
14	IPSL-CM5A-MR	France	Institut Pierre Simon Laplace, France	2.5 deg x 1.25 deg
15	IPSL-CM5B-LR	France	Institut Pierre Simon Laplace, France	2.75 deg x 1.8 deg
16	MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies,and Japan Agency for Marine-Earth Science and Technology	1.4 deg x 1.4 deg
17	MIROC-ESM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
18	MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
19	MRI-CGCM3	Japan	Meteorological Research Institute, Japan	1.1 deg x 1.1 deg
20	NorESM1-M	Norway	Norwegian Climate Center, Norway	2.5 deg x 1.9 deg

Point #6

COMMENT: This study focus on the projection of water table depth at five forest sites. The title should mention “water table depth” rather than “hydrology” which is a broad concept.

RESPONSE: The word “hydrology” was changed to “water table level” in the title.

(2) Comments from anonymous referee #2 and author's response:

RESPONSES TO REVIEWERS' COMMENTS

We are grateful to the reviewers and associate editor for their detailed and insightful comments. In light of the suggestions, we have made efforts to significantly revise the manuscript. The suggestions and comments have substantially contributed towards improving the paper. More details are as follows:

Interactive comment on "Modeling the Potential Impacts of Climate Change on the Hydrology of Selected Forested Wetlands in the Southeastern United States" by Jie Zhu et al.

Anonymous Referee #2

Received and published: 17 May 2017

GENERAL COMMENTS: The discussion paper uses an empirical approach to determine hydrological effects on climate change for 5 wetland types in the southeastern U.S. The paper generally has scientific significance in that it tries to address uncertainties associated with climate change, and the overall structure of the paper is clear and concise. However, the paper lacks rigorous evaluation of the model and results. The general model structure appears flawed (see comments below), and model results are seemingly taken at face value. For example, the authors do not address a major source of uncertainty associated with climate change: water use efficiency (WUE). Climate change is associated with increases in CO2, not just temperature, and increased CO2 is known to increase WUE, which would have major implications for the results presented here. There was also little consideration given to changes in water availability for vegetation, which drives actual ET. Additionally, the graphics and tables were lacking in quality and readability, and should be revised. There were many typographical and grammatical errors. Overall, this paper needs major revisions.

RESPONSE: We are very thankful for the reviewer's detailed reviews about the uncertainty associated with our modeling results related to other factors of future climate change, e.g. the increased WUE because of the increased CO_2, and the changes in water availability for vegetation. This work focuses on the wetland groundwater variability due to climate drivers' change such as precipitation and air temperature. We did not specifically consider the effects of increased CO_2 on vegetation growth and productivity which may further affect wetland hydrology in the study due to the following reasons. First, some of the GCM models used here already contain a dynamics vegetation model (e.g., Yu et al., 2016); thus, vegetation responses to increased CO_2 have been considered in these GCMs. Second, previous results suggest that precipitation and surface air temperature are the two first order climate variables to drive wetland groundwater (Liljedahl et al., 2011). Third, quantitative analysis about the wetland evaporation/evapotranspiration comparison found that transpiration from canopy provided few contributions to evapotranspiration (Li et al., 2009). We thank the reviewer to get our attention and will study the aspect in our future work although this is out of the scope of work of the present study. According to the comment, we added recommendations for future work in line 386-387 (in the revised manuscript, similarly hereinafter). The related references were as follows:

Li, Y. J., Zhou, L., Xu, Z. Z., and Zhou, G. S.: Comparison of water vapour, heat and energy exchanges over agricultural and wetland ecosystems, Hydrological Processes, 23, 2069-2080, 2009.

Liljedahl, A. K., Hinzman, L. D., Harazono, Y., Zona, D., Tweedie, C. E., Hollister, R. D., Engstrom, R., and Oechel, W. C.: Nonlinear controls on evapotranspiration in arctic coastal wetlands, Biogeosciences, 8, 3375-3389, 2011.

Yu, M., G. Wang, and H. Chen, Quantifying the impacts of land surface schemes and dynamic vegetation on the model dependency of projected changes in surface energy and water budgets, J. Adv. Model. Earth Syst., 8, 370–386, 2016.

We have also improved the methodology, results, and discussion re-plotted the graphs using high resolution and re-done the tables to improve the quality and readability as suggested (details see the marked version).

SCIENTIFIC COMMENTS:

For the reviewer's convenience during re-review, we numbered his/her comments and included our corresponding responses, below.

Point #1

COMMENT: Line 78-79: Why is Greenberg et al. (2015) referenced here without discussing how it "satisfactorily" used an empirical model? All you say is that they used one.

RESPONSE: We much appreciate the reviewer's careful review. We further discussed the references in line 70-73 as follows:
"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."

Point #2

COMMENT: Line 158-159: It is not clear what the rationale is for using lagged water table as an independent variable? It seems clear that the most recent water table value will be highly correlated to the water table now. Is this just using autocorrelation as a covariate? Consider revision.

RESPONSE: The lagged water table was actually considered as a covariate. The rationale to use the lagged water table was to account for its contribution to the current water table, in addition to the role of current climate and water availability, based on the considerations as follows:

(i) This study adopted the well-established methodology of dynamic panel model widely used in statistics and econometrics. The dynamic panel modeling includes the first lag dependent variable coupled with the explanatory variables (e.g. P, PET, in this study). The model structure with a given lag effect were successfully used in the previous 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 modelling (Liu et al., 2017; Ozturk, 2015). Lyman's (1992) and Ozturk (2015) confirmed the adjustments significance of minimizing heterogeneity in the traditional Ordinary Least Squares assumptions by including the first lagged dependent variable. Webb et al. (2003) improved the sensitivity and explanatory power of the hourly based water-air temperature regression models by incorporating a lagged response of water temperature. In a wetland hydrology and climate change study, Greenberg et al. (2015) successfully forecasting the hydroregimes of multiple wetlands by modeling the water table depth using water level of the prior week and precipitation as predictors of current water table.

(ii) The statistical model structure has physical meaning and can be viewed from the perspective of water balance. A lagged effect of water table was supported by the water balances and the water table dynamics of wetlands. It is due to the fact that wetland groundwater has memories which can be carried beyond the next season as to influence the water balance in the coming years (Miguez-Macho and Fan 2012). Firstly, the water balance of the five selected wetlands can be written as $WT_t - WT_{t-1} = \alpha + \beta(P_t - ET_t) + \varepsilon_t$. It indicates the causality balances between water tables changes (left side terms of the above equation i.e., $WT_t - WT_{t-1}$) and its water availability changes (right side terms of the above equation). The item of WT_{t-1} depending on the time scale can be considered as the memory effect of water tables. By moving the memory item (WT_{t-1}) to the right side, the different statistical coefficient of WT_{t-1} can reflect the different memory characters/effects in the five selected wetlands. Based on these reasons, we believe the model structure that includes a lagged water table in this study can offer more information concerning not only water tables changes due to changes in climate variables, but also the different memory effects of different wetlands in this region.

(iii) All the information is not contained in the antecedent water table conditions of wetlands. The lagged water table only offers the basis for the current condition, however, the forcings (e.g. climate and water availability in this study) alters the water table depth. In another word, the water table depth would always decrease/increase along with a given initial discharge/recharge condition for the wetland. But, a wetland actually alternatively discharges or recharges for the flatness, thus water tables fluctuated with the forcings. Therefore, both the forcings and the lagged water table would determine the water tables for a wetland. What's more, when using the water table at LP site with forcings from FL-WET site, the statistics show that in spite of the same antecedent condition, the R^2 becomes poorer to 0.54 from 0.83.

(iv) From the perspective of the proved wide-sense stationary first-order autoregressive process of water tables in the five selected wetlands, the variance will not change with the autoregressive process introduced into the statistic model. For an autoregressive process given by: $Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t$, where ε_t is a white noise process with zero mean and constant variance σ_ε^2. The first-order autoregressive process is wide-sense stationary when and only when $|\beta|<1$, because it is the output of a stable filter with a white noise input (Mills, 1990). In the wetlands analyzed in the study, the coefficient of WT_{t-1} are<1 (Table 3), indicating a wide-sense stationary autoregressive process of water table. Thus the variance of the process does not change with simulation over time, and the intertemporal effect ($\beta^n \varepsilon_1$) of shocks diminishes toward zero in the limit.

(Ⅴ) From the perspective of the independence of the explanatory variables, introduce of antecedent water table does not violate the independence requirements among the explanatory variables. Independence between the explanatory variables was satisfied since correlation coefficient between P-PET and WT_{t-1} was very poor (<2.7) for the five selected wetlands in the study.

According to the comment, the justification was further concisely added in line 161-166 in the revised manuscript to make it clearer for readers. Also, the related new references were added to the revised manuscript as follows:

“Almendarez-Hernández, M., Avilés Polanco, G., Hernández Trejo, V., Ortega-Rubio, A., and Beltrán Morales, L.: Residential Water Demand in a Mexican Biosphere Reserve: Evidence of the Effects of Perceived Price, Water, 8, 428, 2016. (Line 432-436)

Arbués, F., Barberán, R., and Villanúa, I.: Price impact on urban residential water demand: A dynamic panel data approach, Water Resour Res, 40, 2004. (Line 442-443)

Arbues, F., Garcia-Valinas, M. A., and Villanua, I.: Urban Water Demand for Service and Industrial Use: The Case of Zaragoza, Water Resour Manag, 24, 4033-4048, 2010. (Line 444-445)

Liu, G., Yang, Z., Tang, Y., and Ulgiati, S.: Spatial correlation model of economy-energy-pollution interactions: The role of river water as a link between production sites and urban areas, Renewable and Sustainable Energy Reviews, 69, 1018-1028, 2017. (Line 542-544)

Lyman, R. A.: Peak and off-peak residential water demand, Water Resour Res, 28, 2159-2167, 1992. (Line 554)

Mills, Terence C. Time Series Techniques for Economists. Cambridge University Press, 1990. (Line 568)

Ozturk, I.: Sustainability in the food-energy-water nexus: Evidence from BRICS (Brazil, the Russian Federation, India, China, and South Africa) countries, Energy, 93, 999-1010, 2015. (Line 595-596)

Webb, B., Clack, P., and Walling, D.: Water–air temperature relationships in a Devon river system and the role of flow, Hydrological processes, 17, 3069-3084, 2003. ” (Line 656-657)

Point #3

<u>COMMENT</u>: Line 160: It seems like an autocorrelation covariance structure should be used given the time-series nature of the data.

<u>RESPONSE:</u> We view that "an autocorrelation covariance structure" here as "covariance structure of autocorrelation". For an autoregressive process given by: $Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t$, where ε_t is a white noise process with zero mean and constant variance σ_ε^2. The autocovariance is $B_n = E(X_{t+n}X_t) - \mu^2 = \frac{\sigma_\varepsilon^2}{1-\beta^2}\beta^{|n|}$, where μ is the model mean, and n is the time step (Mills, 1990). In this study, autoregressive process is wide-sense stationary ($|\beta|<1$), thus $\frac{\sigma_\varepsilon^2}{1-\beta^2}\beta^{|n|}$ diminishes toward zero in the limit in the general model form (Line 180). Besides, the autocorrelation nature for the given data time-series was first tested to select the final variables. The autocorrelation of water tables with lag time of 0 day, 15 days, 30 days, 45 days, and 60 days were tested, as well as their correlations with the other explanatory variables. Consequently, in the final model (line 217), only the 15-day (one time step) lagged water table was chose as an explanatory variable for the best statistical results. Thus only a constant variance σ_ε^2 exists in the final selected wide-sense stationary first order autoregressive process.

Point #4

<u>COMMENT</u>: Line 176: Water loss is also controlled by net groundwater flow, but more importantly by vegetation access to water and vegetation water use efficiency (WUE), which are not accounted for in the model. And because we know that WUE is strongly influenced by CO2 concentrations, this appears to be a major deficiency in the model.

<u>RESPONSE:</u> Please see our replies to the General Comment (page 1-2). We agree with reviewer on the hydrological processes identified. However, given the empirical nature of our model, these factors are not explicitly considered. We have also added some discussion regarding the potential uncertainty originating from discounting the effects of increase in CO_2 on WUE in the revised version (see lines 386-387):
"For example, an increase in atmospheric CO2 concentration is likely to increase plant water use efficiency and thus the ET and water balance of wetlands (Brummer et al., 2012)"

The related new reference was added to the revised manuscript as follows:

"Brummer, C., Black, T. A., Jassal, R. S., Grant, N. J., Spittlehouse, D. L., Chen, B., Nesic, Z., Amiro, B. D., Arain, M. A., Barr, A. G., Bourque, C. P. A., Coursolle, C., Dunn, A. L., Flanagan, L. B., Humphreys, E. R., Lafleur, P. M., Margolis, H. A., McCaughey, J. H., and Wofsy, S. C.: How climate and vegetation type influence evapotranspiration and water use efficiency in Canadian forest, peatland and grassland ecosystems, Agricultural and Forest Meteorology, 153, 14-30, 2012." (Line 457-461)

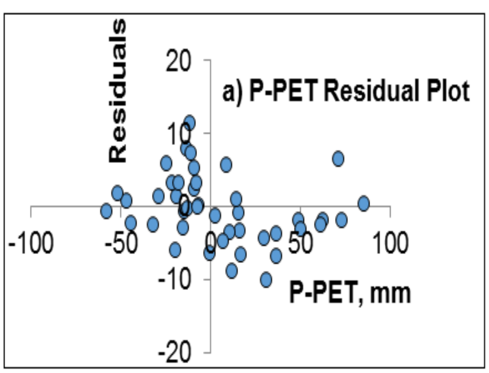
Point #5

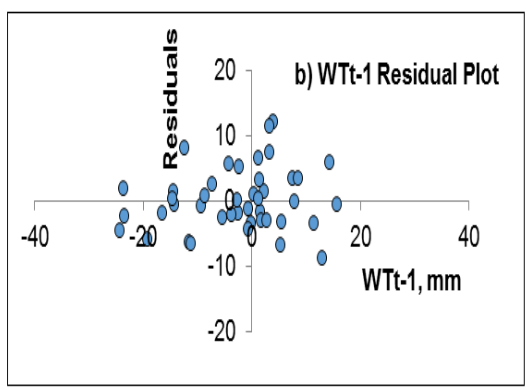
COMMENT: Line 186-195: Did you also test for assumptions of normality of residuals and homoscedasticity of residuals? If you did not take into account autocorrelation of covariance it is likely that these assumptions may be violated.

RESPONSE: The normality and the homoscedasticity for both the five sites were tested before the models were applied to the prediction. The residual plots of the five specific models showed that errors are homoscedastic, and both the residuals and the normal probability plot showed the normality of the residuals in the five selected wetlands. With introducing the autoregressive variable, the Durbin's h also indicated the autocorrelation disturbance process. We also added the clarification to the revised version in line 191, and line 220-221:

"Also, the autocorrelation disturbance process was tested by Durbin's *h* statistic (*Bhargava et al.*, 1982)." (Line 191)

"Durbin's h statistic showed that all five wetland regressions support the autocorrelation disturbance process." The related figures of AR site were shown as an example as follows: (Line 220-221)





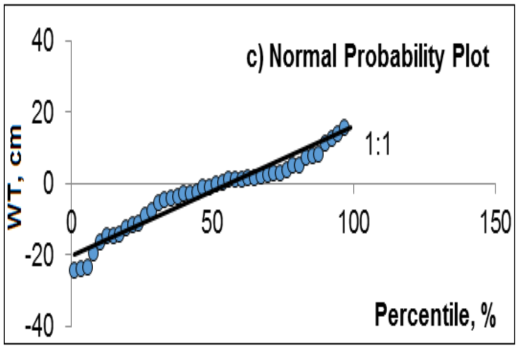


Figure 1 Residuals and normal probability plots of AR site, a) P-PET residual plot, b) WTt-1 residual plot, c) normal probability plot. The residuals and standard residuals of the observed Y (water table) have a mean of zero (6×10^{-16}， 1×10^{-16}， respectively).

Point #6

<u>COMMENT</u>: Lines 196-199: What did you find with Durbin's h? Did it support autocorrelation or not?

<u>RESPONSE:</u> The Durbin's h tests for the models showed that all the five wetlands regression models support the autocorrelation, by comparing the lower and upper critical value from the Durbin-Watson Table. The results of DW test (2.59 for AR, 2.66 for LP, 1.32 for FL-UP, 2.63 for FL-WET, and 1.49 for SC) showed that all five wetland regressions support the autocorrelation disturbance process. We also added the statement to the revised manuscript in line 220-221.

Point #7

<u>COMMENT</u>: Line 234-236: Are these estimates for changes to PET based purely on temperature changes? This seems important to note.

<u>RESPONSE:</u> Yes, PET is estimated based on air temperature only in addition to day length following Sun et al., (2002). The associated note was added in line 167-170 as follows:
"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)."

The new reference was added to the revised manuscript as follows:

"Hargreaves, G. H. and Samani, Z. A.: Estimating potential evapotranspiration, Journal of the Irrigation and Drainage Division, 108, 225-230, 1982." (Line 515-516)

Point #8

COMMENT: Line 270-271: This sentence is the opposite of what is suggested by the figure and is confusing to interpret.

RESPONSE: The sentence was revised in line 278-282 as follows;

"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 RCP 8.5 scenario, as well as in the baseline scenario (Table 5, Fig. 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 RCP 8.5 scenario."

Point #9

COMMENT: Lines 272-279: This section is very difficult to understand, especially trying to reconcile with figures. Suggest re-writing.

RESPONSE: The section has been re-written (Line 283-290) as follows:

"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 RCP 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 RCP 8.5 scenario (Table 5, Fig. 6)."

Point #10

__**COMMENT**__: Lines 283-285: Where are the R2 values coming from? Are these ratios of R2 to other sites? Clarification needed.

__**RESPONSE:**__ The R^2 values are the coefficient of determination of the regressions model results. The clarification was added in the revised version in line 293-296 as follows: "The lower R2 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."

Point #11

__**COMMENT**__: Line 288: Did you statistically test that the model coefficients were similar? They do not seem too similar to me…

__**RESPONSE:**__ We much appreciate the reviewer's careful review. The sentence was deleted in the revised version.

Point #12

__**COMMENT**__: Where is the discussion of how the model did not perform well? The model appears to be much flashier and tends to overpredict relative to observed data? RMSE or some other metric would be useful as a comparison.

__**RESPONSE:**__ We have addressed reviewer's concerns by adding RMSE values. The discussion was added in line 231-237 and line 195 as follows:

“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, …” (line 231-237).

“Limited data availability can contribute to model deficiency.” (Line 195).

TECHNICAL CORRECTIONS:

Point #1

COMMENT: Line 56: “… and more powerful hurricanes landfall.” Word choice here is awkward.

RESPONSE: In line 49, the phrase was revised to “more intense Atlantic hurricanes”.

Point #2

COMMENT: Line 58: “process-based study” should be “process-based studies”.

RESPONSE: The phrase was revised to “process-based studies” in the updated version.

Point #3

COMMENT: Line 70: add “and” before “…their potential uses…”

RESPONSE: The “and” was accordingly added.

Point #4

COMMENT: Line 73-75: This sentence needs revision for clarity and grammar.

RESPONSE: The sentence was revised in line 65-67 as follows:
"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 and acceptable performance when applied over multiple sites."

Point #5

COMMENT: Line 75: "Performance such type of models…" a word is missing.

RESPONSE: The sentence was revised as "Especially, performance of such empirical models…" in line 67-68.

Point #6

COMMENT: Line 84: change "increased" to "subsequent increases".

RESPONSE: The word was changed accordingly in line 68.

Point #7

COMMENT: Line 88: There is an extra "s" after the parentheses.

RESPONSE: The extra "s" was deleted in the revised version.

Point #8

COMMENT: Line 289: change "higher" to "lower".

RESPONSE: The word was accordingly changed to “lower”.

Point #9

COMMENT: Line 387: Missing a word in “Climate change from single has been used…” and “wetalnd” is misspelled.

RESPONSE: The sentence was revised as “Climate data from single GCMs (Greenberg et al., 2015; Wang et al., 2015) have been used in wetland hydrological response, …” in line 404-405.

Point #10

COMMENT: Line 625: Table 1 should have consistent formatting for each of the data in columns for ease of comparison. Consider a more generic description of soils instead of series names.

RESPONSE: The Table 1 was reformatted and revised in line 670, and a more generic description of soils instead of series names were used for the sites. The climate data from different time series including the most of the observation years is to better reflect different climate background during model development.

Point #11

COMMENT: Line 670: Figure 3(d) what is meant by the orange dots?

RESPONSE: Figure 3 (line 705, as follows) was updated in the revised version with mistake fixed and the site names put in the figure panel itself. We also improved the quality of Figure 1 (line 690, as follows) and Figure 2 (line 700, as follows).

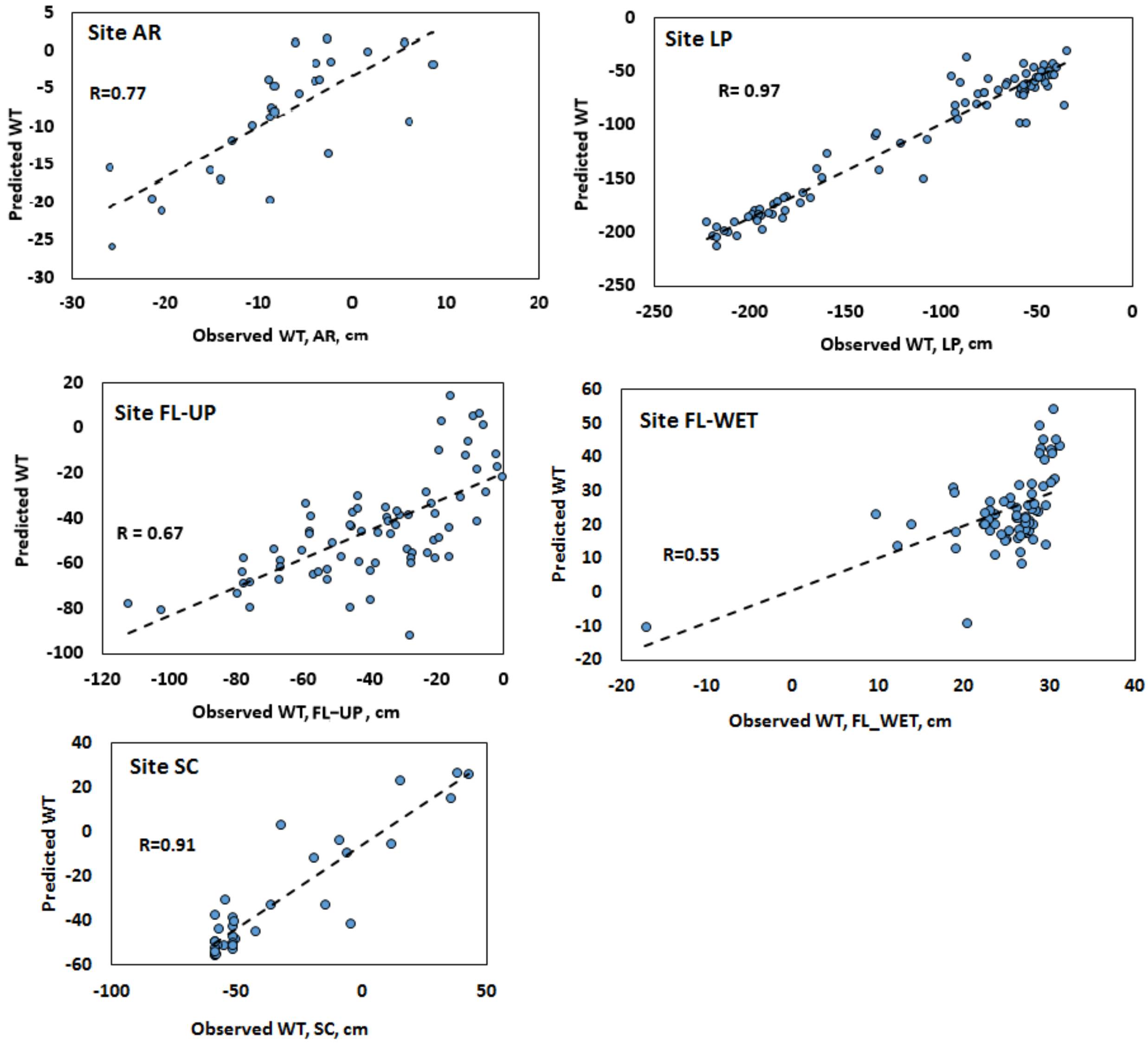


Fig. 3 Scatter plots of the observed and predicted mean water table in five wetlands in the Southeastern United States (unit: cm), Dashed lines are 1:1 line.

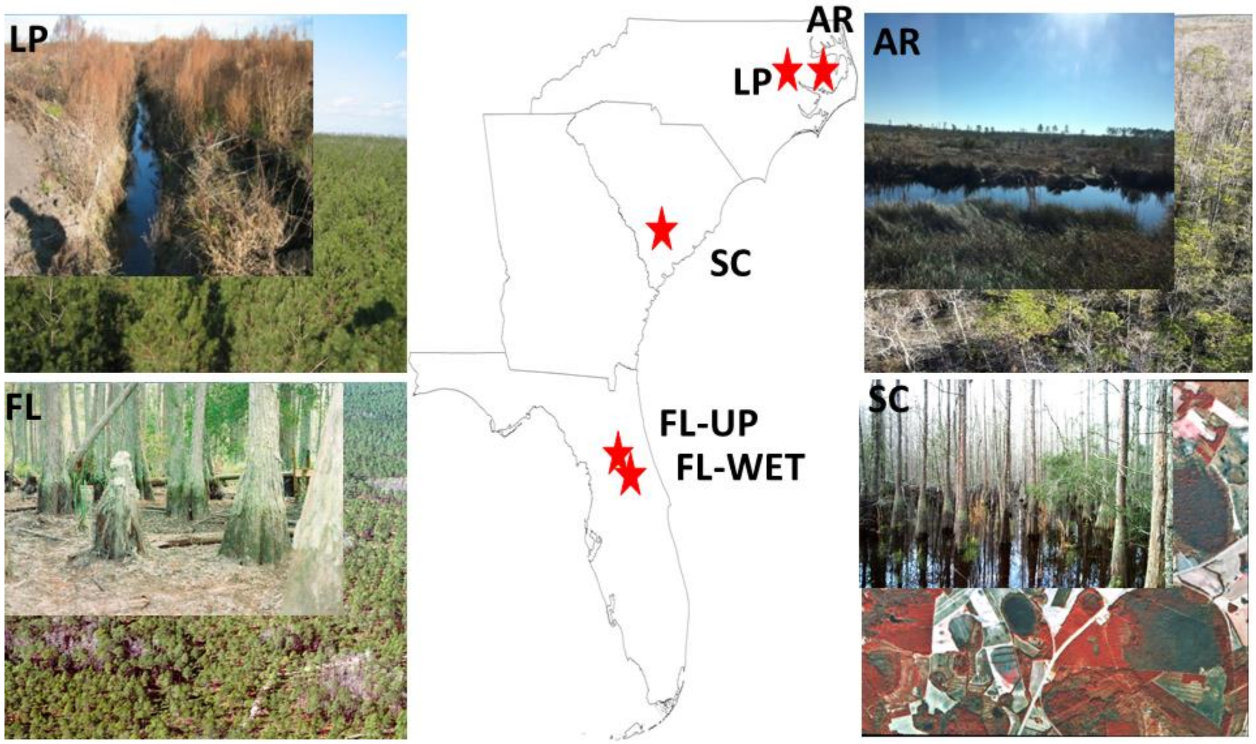


Fig. 1 Study area, where the star symbol marks the study site location. Wetland AR: wetland of Alligator River National Wildlife Refuge in North Carolina; wetland LP: wetland of loblolly pine plantation in North Carolina; wetland SC: wetland in South Carolina; wetlands in Florida: wetland FL–UP (upland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

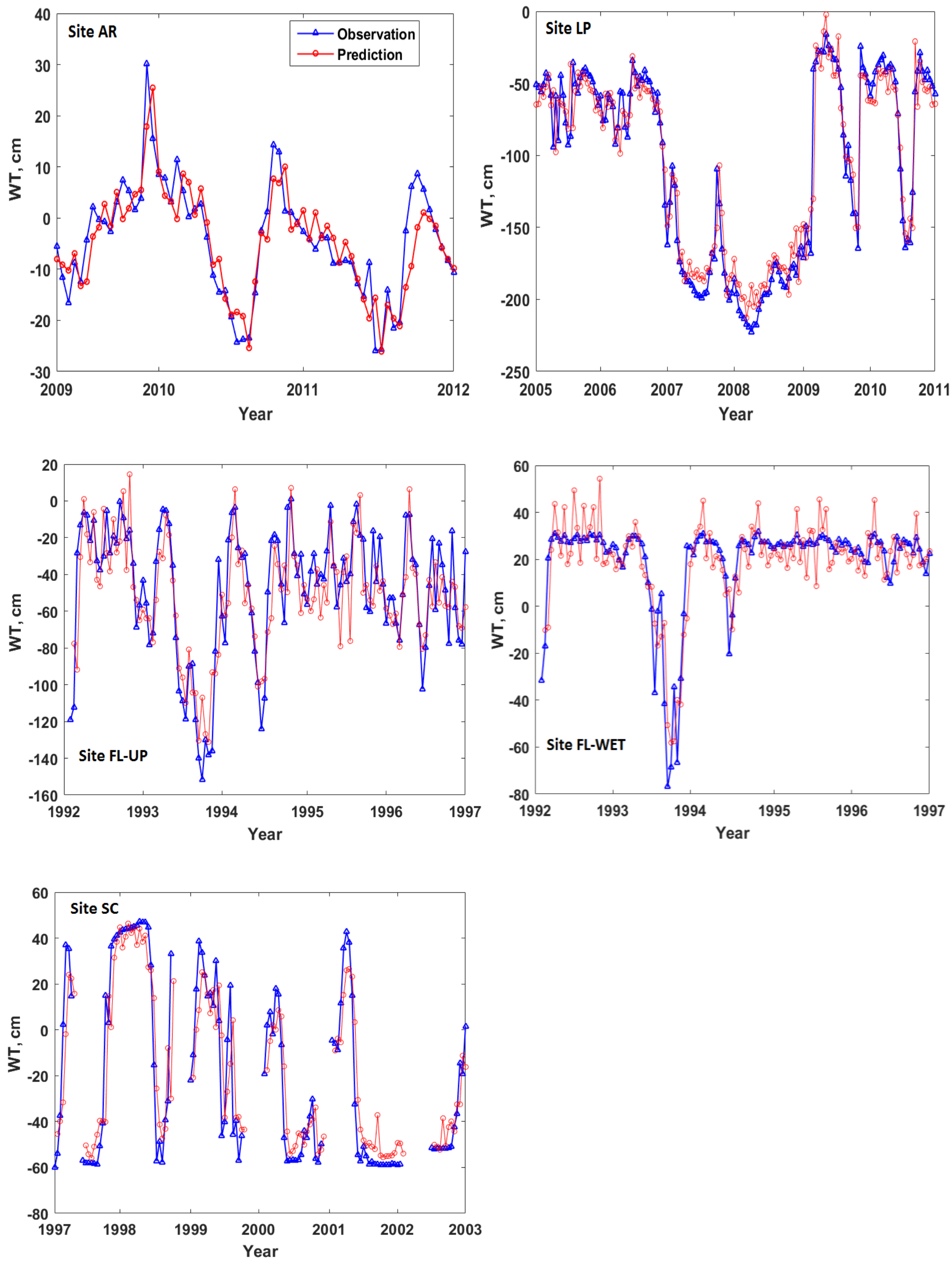


Fig. 2 Comparison of observed and simulated15-day water table in five wetlands in the Southeastern United States, WT is water table.

Point #12

<u>COMMENT</u>: Line 680 and 685: Figures 4 and 5 are begging to have significance letters attributed to each boxplot.

<u>RESPONSE:</u> We much appreciate the reviewer's careful review. The Figures 4 and 5 were revised in line 710 (as follows) and line 720 with significance letters, site names in the panel itself, and the quality was improved as well.

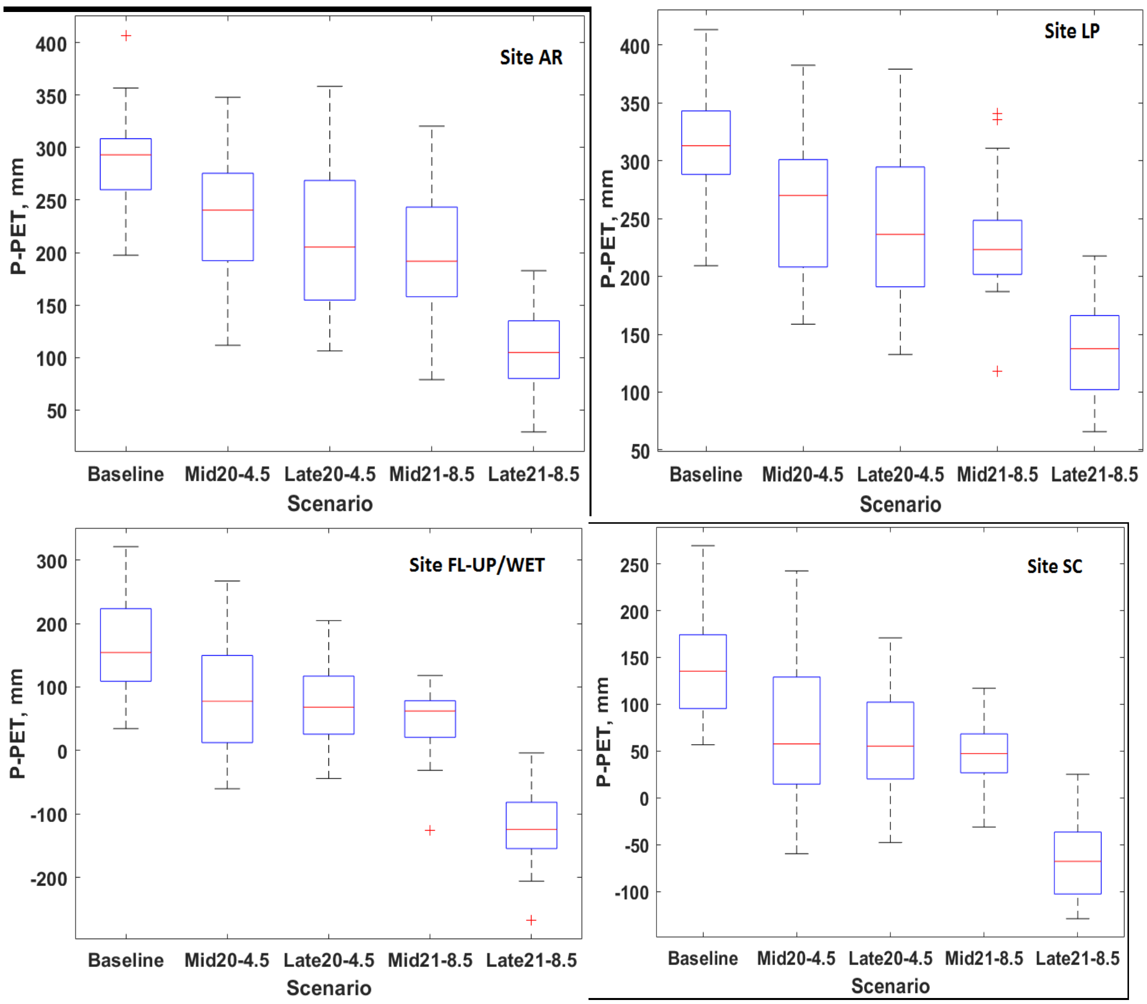


Fig. 4 Total annual precipitation minus potential evapotranspiration of 20 GCMs in five wetlands in the southeastern United States (unit: mm).

Note: Baseline: 1980–1999, historical run of GCMs;

Mid 20-4.5: 2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;

Mid 21-8.5: 2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;

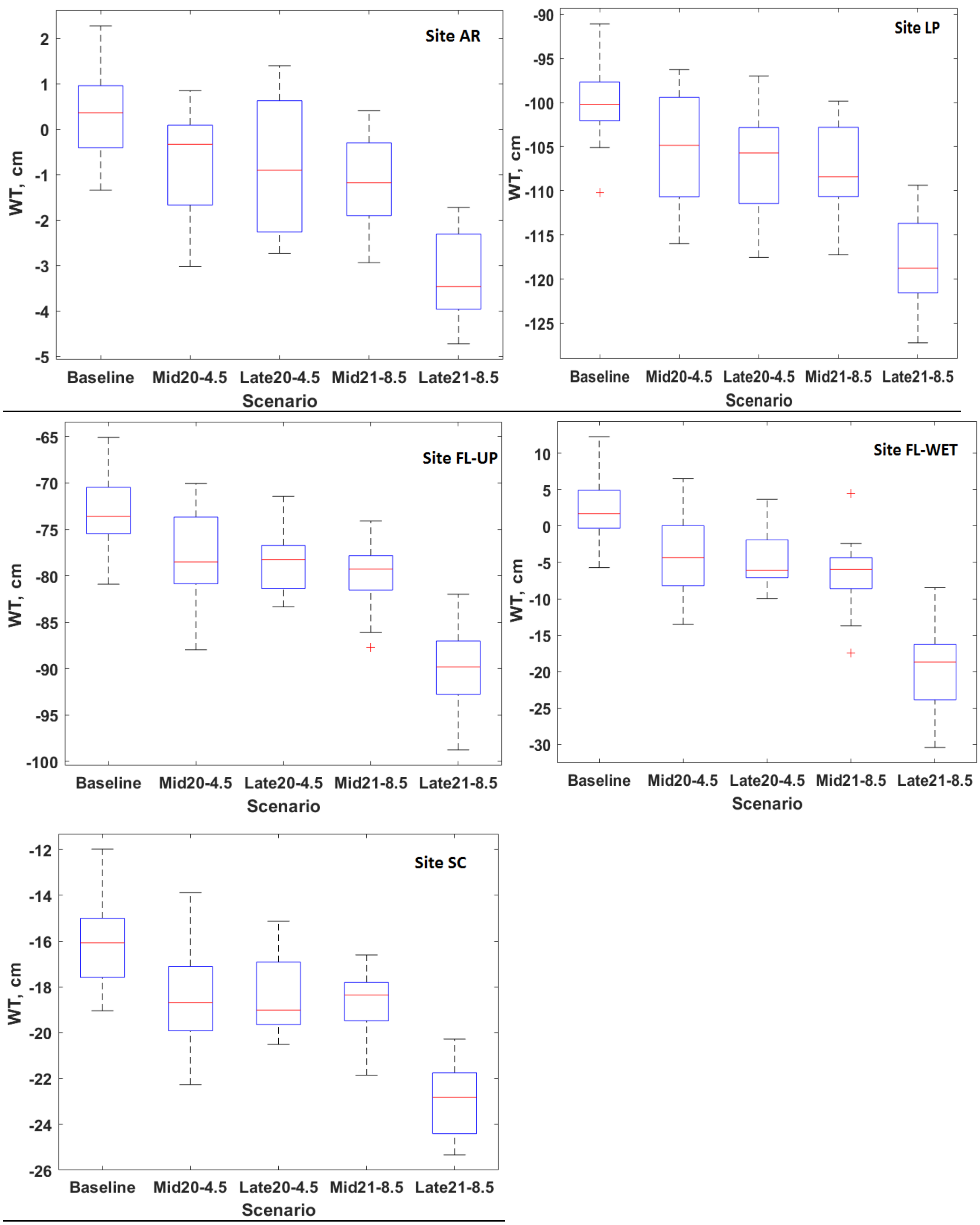


Fig. 5 Mean predicted annual water table of 20 GCMs in five wetlands in the southeastern United States (unit: cm).

Note: Baseline: 1980–1999, historical run of GCMs;

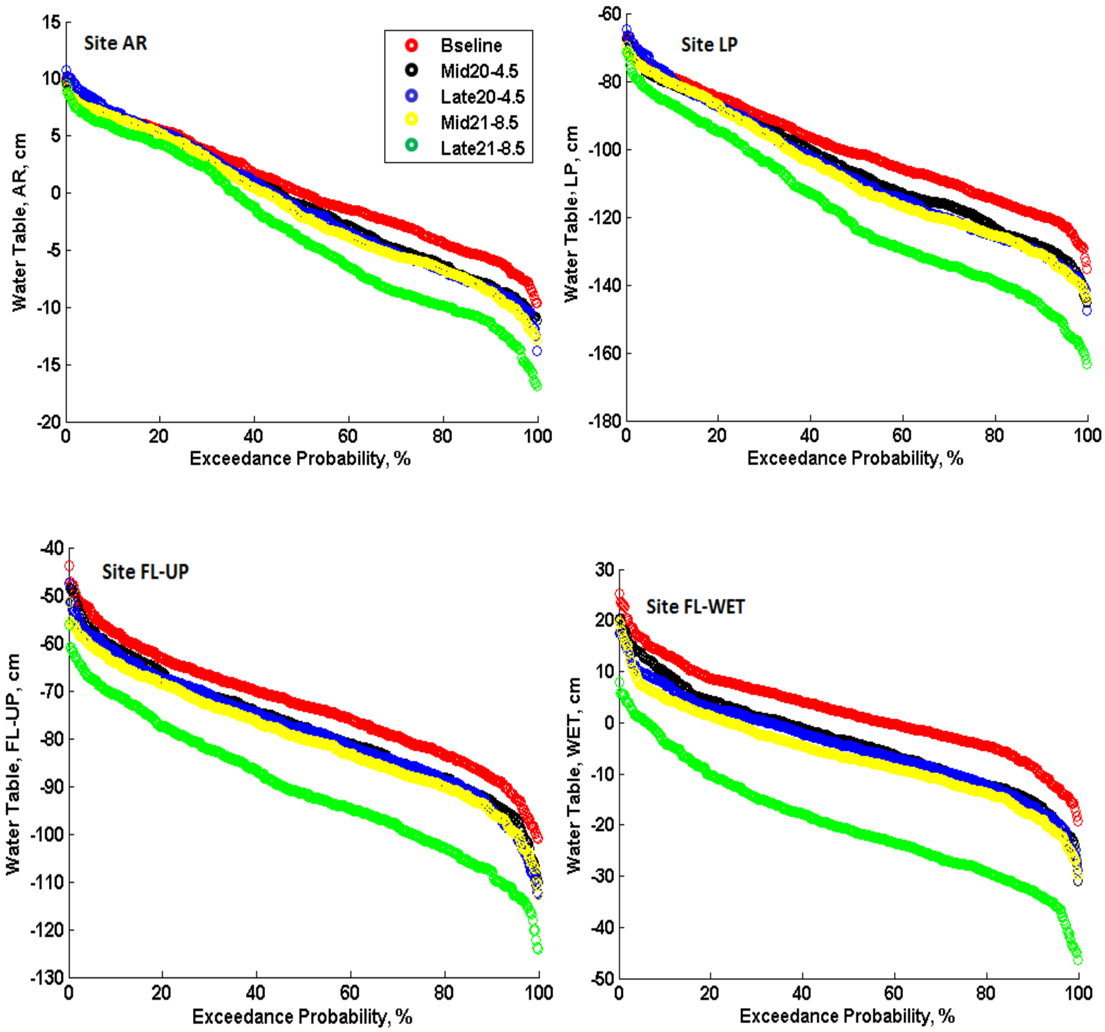
Mid 20-4.5: 2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;

Mid 21-8.5: 2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;

Point #13

COMMENT: Line 685: Figure 6 – These axes should be flipped for ease of interpretation. Also fix the legend so it doesn't look like it was drawn by hand. Consider changing the x-axis label and putting the site name in the figure panel itself.

RESPONSE: We much appreciate the reviewer's careful review. The Figure 6 was revised with fixing the axes, legend, label, and site names. Also, the figure quality was improved in the revised version in line 730 as follows.



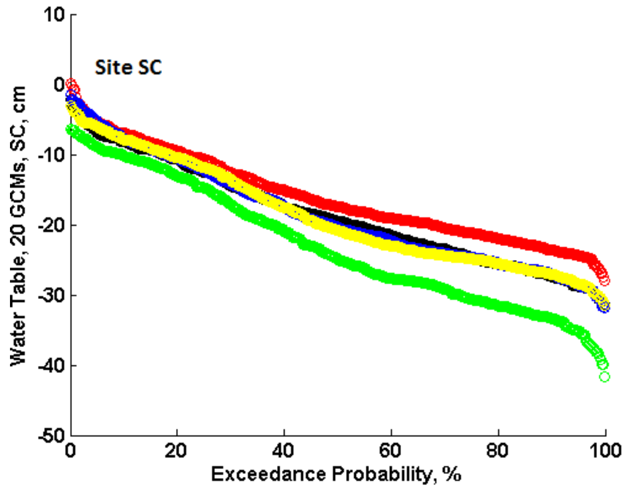


Fig. 6 Exceedance probability of the mean predicted water table in the growing season of 20 GCMs in five wetlands in the Southeastern United States (unit: cm).
Note: Bseline:1980–1999, historical baseline period;
Mid 20-4.5:2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;
Mid 21-8.5:2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;

(3) Author's changes in manuscript

Modeling the Potential Impacts of Climate Change on the Water Table Level of Select 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 Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios. We show that combined projected 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.

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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 wetland hydrology in regulating ecosystem function has long been recognized (*Sun et al.*, 2000). Wetland hydrology 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 depth, may have profound impacts on wetland structure and other ecosystem functions (*Webb and Leake*, 2006).

Wetland hydrology 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). Wetland hydrology 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 °C 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 °C (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 and acceptable performance when applied over multiple sites. The performance of empirical models in climate change studies appears to be powerful when incorporating downscaled Global Climate Model (GCM) outputs (*Sachindra et al.*, 2013; *Li et al., 2016*). For example, *Li et al.* (2016) used log-linear models for 21 rainfall stations and severn hydrometric stations to predict hydrological drought. Greenberg et al. (2015) developed an empirical model and demonstrated its utility for climate-change planning by forecasting

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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., hydroperiod). Future climate data from 20 GCMs participating in the Coupled Model Inter-comparison Project 5 (CMIP5) under both Representative Concentration Pathway (RCP) 8.5 and RCP 4.5 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 (Fig. 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

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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 the precipitation, air temperature, wind speed, net radiation, and other canonical meteorological factors. The daylight duration data were from The United States Naval Observatory (USNO) (http://aa.usno.navy.mil/data/docs/Dur_OneYear.php). 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):

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

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 mean daily air temperature (AT, ℃) calculated by the equation modified from Dingman (2015):

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

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 mean daily climate data were derived from the 20 GCMs, a product of the Multivariate Adaptive Constructed Analog (MACA) dataset (Supplementary Table S1) for two future RCP scenarios (RCP 4.5 and RCP 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 GCM 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 GCM 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

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and future climate conditions key to wetland hydrology, including the daily maximum temperature near the surface (2 m), daily minimum temperature near the surface (2 m), 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 the 20 GCMs climate dataset were used. To analyze the historical and future hydroclimatic changes for the full time scale of the GCM 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 GCM climate dataset. The five simulation scenarios include:

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

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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 (Fig. 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*

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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 (Fig. 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, Fig. 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 in RCP 8.5, compared to the historic 1980 to 1999 baseline, is expected to be 3.9 °C, 4.3 °C, 4.0 °C, and 4.4 °C in the future (2080 to 2099) for AR, LP, FL, and SC, respectively (Table 4, Fig. S1). The average increase from the baseline in RCP 8.5 in the five wetlands would be

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approximately 4 °C, 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 RCP 8.5 scenario compared with that of the historical baseline period (Table 4). The increase in PET is expected to be smaller in the RCP 4.5 scenario (Tables S2–S6, Fig. S2). For example, PET of wetland AR would increase by 13 % (130 mm) in the RCP 4.5 scenario (1107 mm), while the increase is 23 % (221 mm) in the RCP 8.5 scenario (1198 mm, Table S2).

The baseline mean annual precipitation was 1266 mm, 1275 mm, 1318 mm, 1192 mm (Tables S2-S6, Fig. S3) for AR, LP, FL, and SC, respectively. The annual total precipitation under RCP 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 RCP 8.5 scenario were smaller than that of the RCP 4.5 scenario (Tables S5–S6). Specifically, the precipitation would increase by 56 mm, 68 mm, and 70 mm (Tables S2-S4) under the RCP 4.5 scenario for wetland AR, LP and SC, respectively.

Future predicted PET will increase more than precipitation, causing a decrease in P-PET for all five wetlands. Specifically, the future annual mean P-PET in the RCP 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 (Fig. 4, supplementary Tables S1–S6). The decrease in P-PET is smaller in the RCP 4.5 scenario. For example, the annual P-PET at AR would decrease by approximately 75 mm (26% of baseline) in RCP 4.5 and 184 mm (64 % of baseline) in RCP 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 wetland hydrology. The annual average water table exhibits a decreasing trend in all the five wetlands predicted by the 20 GCMs under both RCP8.5 and RCP4.5 scenarios (Fig. 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 RCP 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 RCP 4.5 and especially for the RCP 8.5 scenarios (Fig. 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 RCP 8.5 scenario (Fig. 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 (Fig. 6).

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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 RCP 8.5 scenario, as well as in the baseline scenario (Table 5, Fig. 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 RCP 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 RCP 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 RCP 8.5 scenario (Table 5, Fig. 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 wetland hydrology in different wetlands

Although the model structure proved the same in all five wetlands, and had good performance overall, a closer comparison shows differing influences on the wetland hydrology. For example, the future annual water table depths in RCP 8.5 scenario decline the most in wetland FL. This may not only be due to the PET increase, which was

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similar to that of the other three sites (AR, LP, and SC), but also because the precipitation decreased in the wetland FL, while it increased at the other sites.

Future changes in precipitation and PET are predicted to vary between AR and LP. In the RCP 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 the water table so that the hydraulic head of the drain is lower than the hydraulic head of the field water table depth. 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, the 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 RCP 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, our models were able to accurately predict the different water table dynamics for multiple wetland sites 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

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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 °C 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

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Bouma et al. (2014). Temperature increase of 2 °C (projected to be 4 °C 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 by 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 wetland hydrology. 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 wetland hydrology 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 GCM 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 GCMs (*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 GCM 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 the water table level, the developed models are simple but powerful tools to provide useful

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wetland hydrology information under a range of climatic and management conditions. Under future climate change, the decrease in water availability is predicted to be a dominant factor for all five wetlands, resulting in a drier future in the study region, especially for isolated wetlands in late 21st century. This study confirms the hypothesis that climate change may have a significant but varying influence on the hydrology of different forested wetlands in the SE US.

This may serve as a basis for future regional studies to understand the interaction between wetland hydrology and climate and to quantify the role of wetlands in regulating regional water and energy balances. 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)	Organ	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	Organ	Flat	Cypre	(*Lu*,

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		(1992-1996)	s imper greenc	woods: Pond cypress, slash pine, swamp tupelo (wetland); slash pine, saw palmetto, gallberry shrubs (upland)	ss swamps and depression wetlands	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	Carolina bay	(*Pyzoha et al.*, 2008; *Sun et al.*, 2006)

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Table 2 Raw data summary.

Data types	Wetlands	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*

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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, α_{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 RCP 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.

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Table 5 A summary of 15-day water table fluctuations in growing season under future RCP 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 in RCP 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.

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Figures

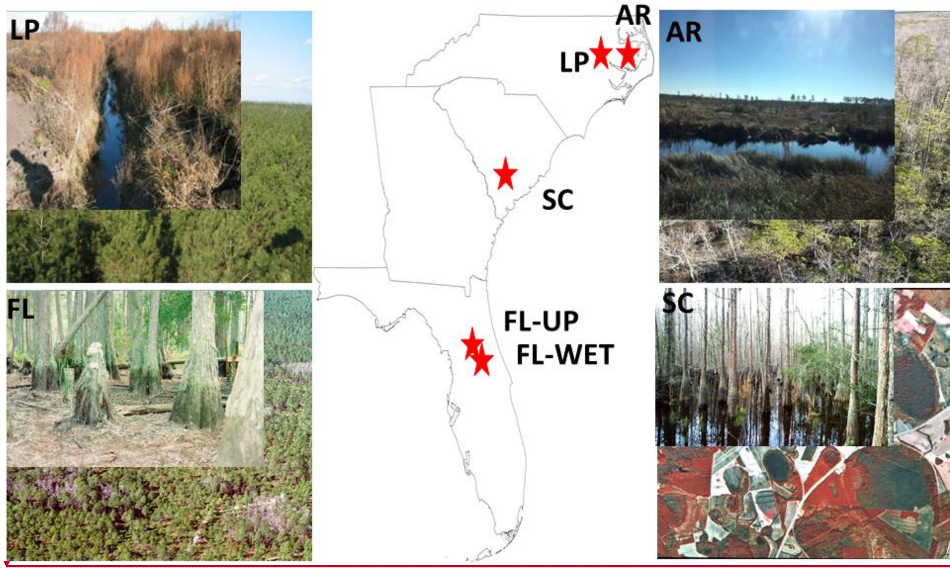

Fig. 1 Study area, where the star symbol marks the study site location. Wetland AR: wetland of Alligator River National Wildlife Refuge in North Carolina; wetland LP: wetland of loblolly pine plantation in North Carolina; wetland SC: wetland in South Carolina; wetlands in Florida: wetland FL–UP (upland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

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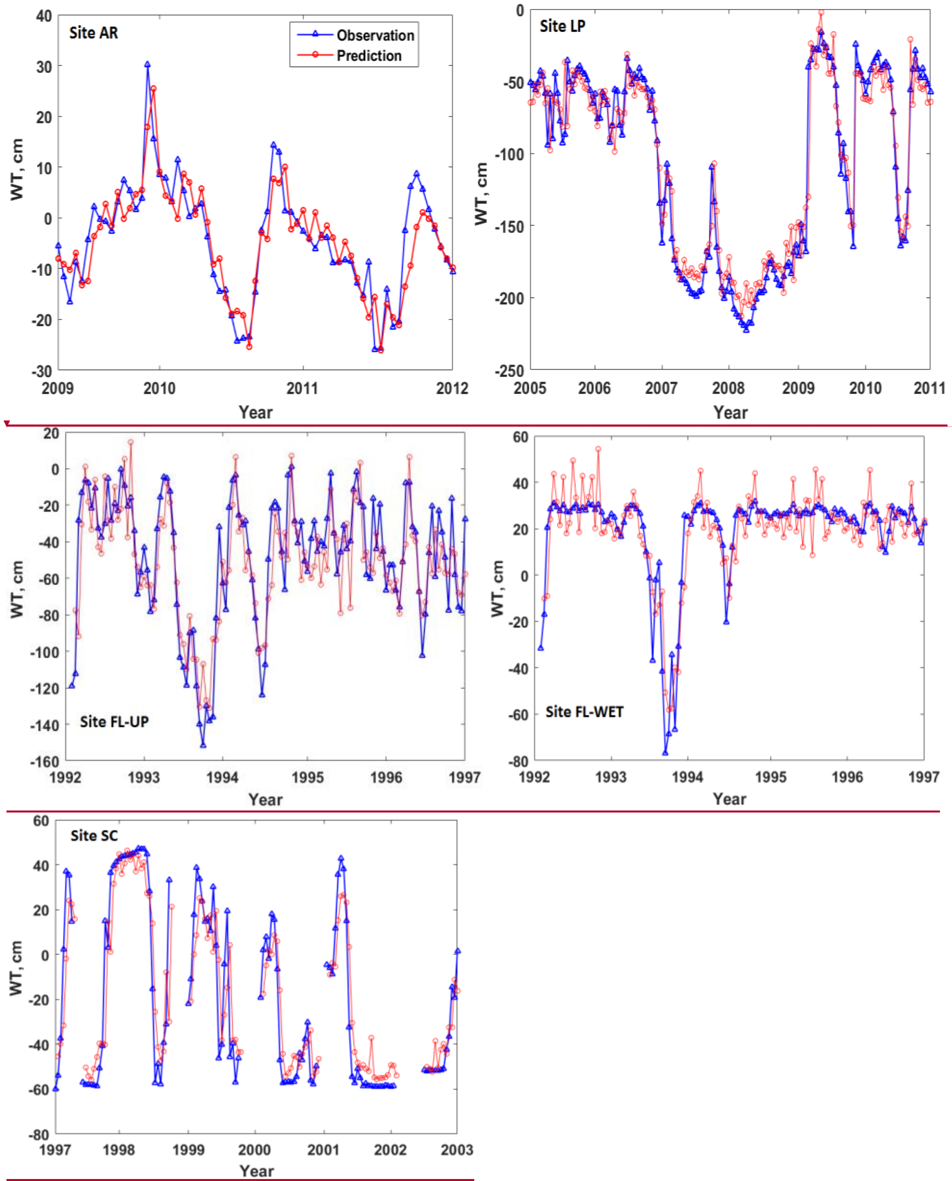

Fig. 2 Comparison of observed and simulated mean water table in five wetlands in the southeastern United States. WT is water table.

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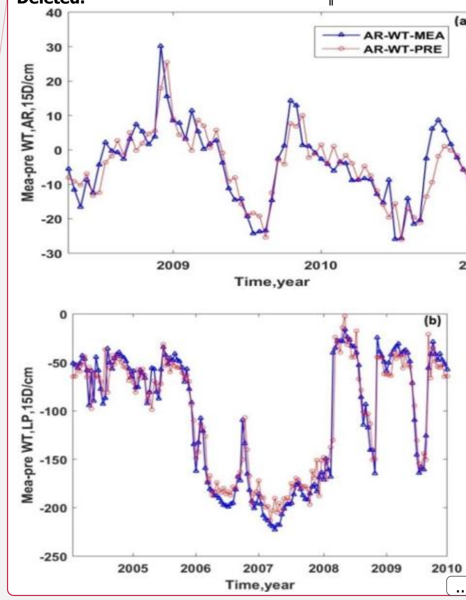

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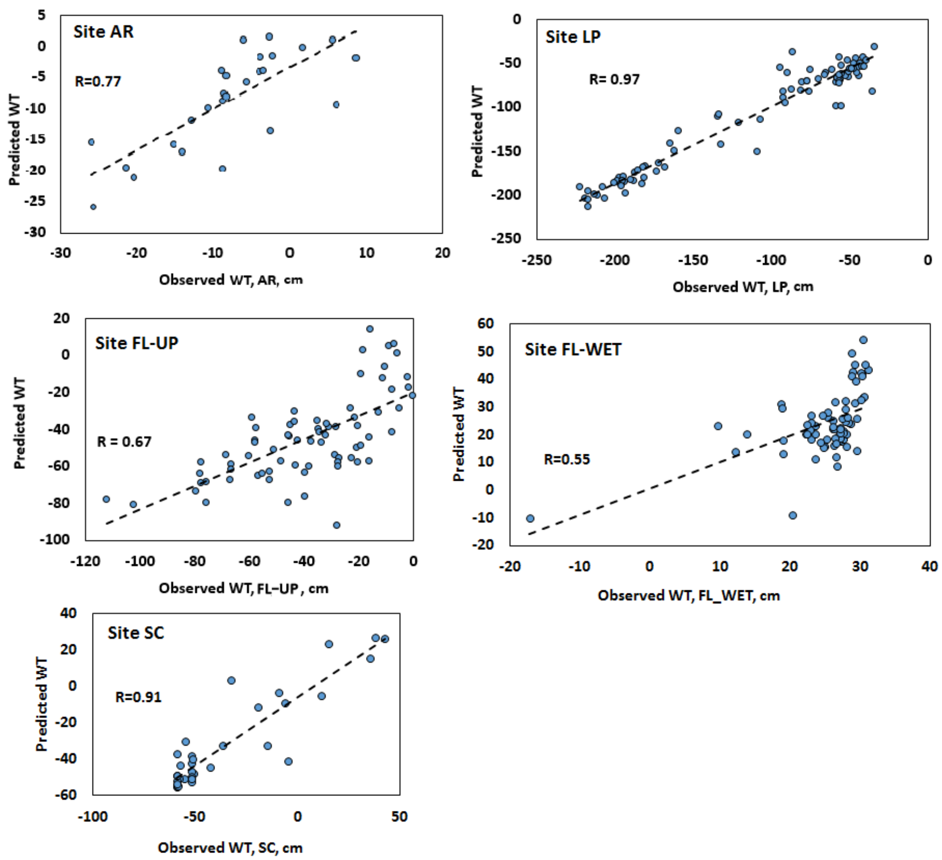

Fig. 3 Scatter plots of the observed and predicted mean water table in five wetlands in the southeastern United States (unit: cm). Dashed lines are 1:1 line.

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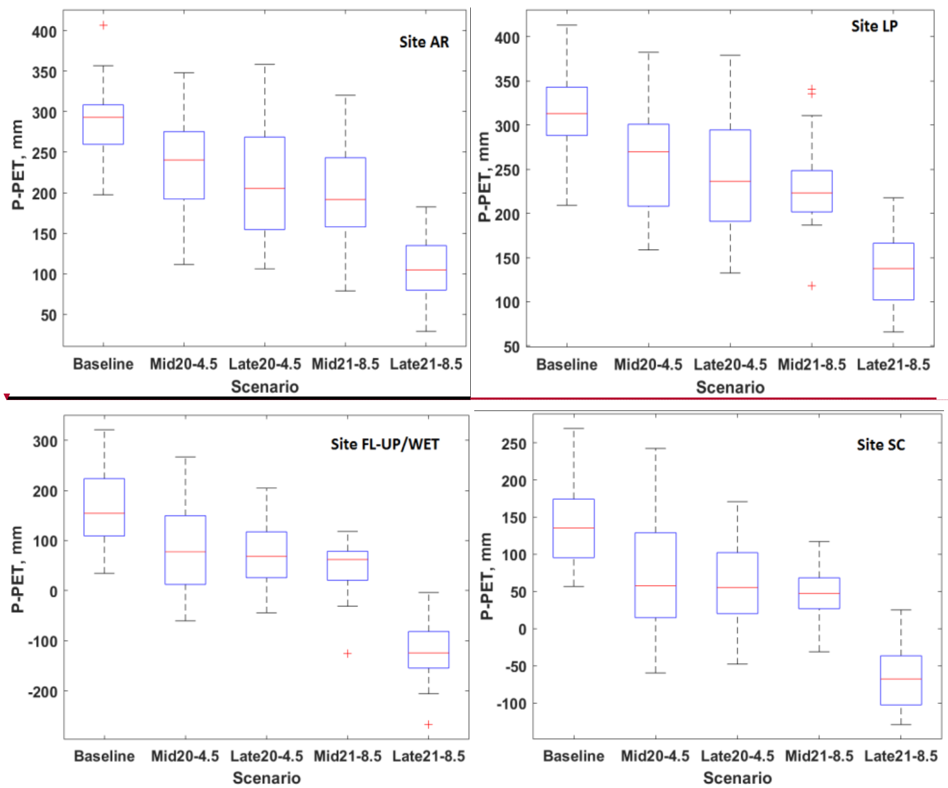
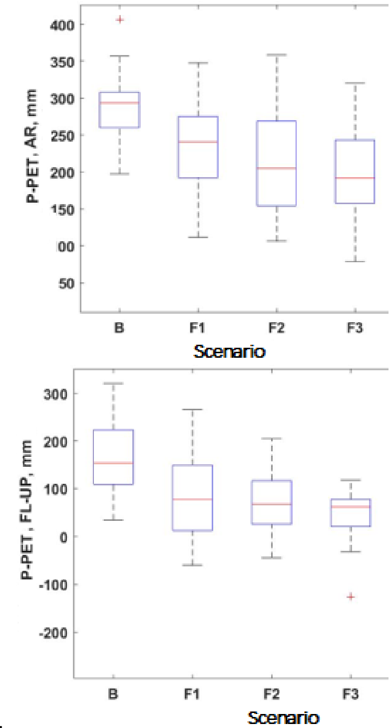


Fig. 4 Total annual precipitation minus potential evapotranspiration of 20 GCMs in five wetlands in the southeastern United States (unit: mm).

Note: Baseline: 1980–1999, historical run of GCMs;

Mid 20-4.5: 2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;

Mid 21-8.5: 2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;



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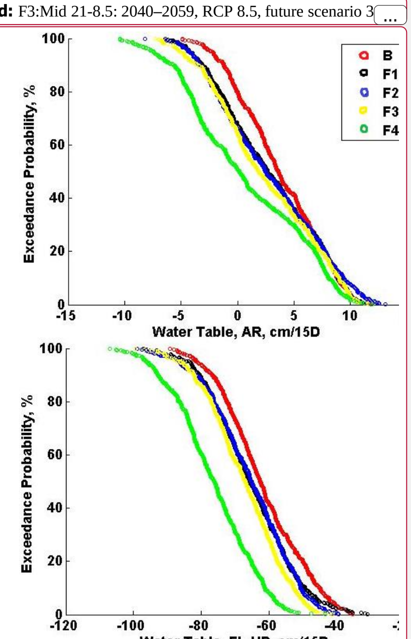

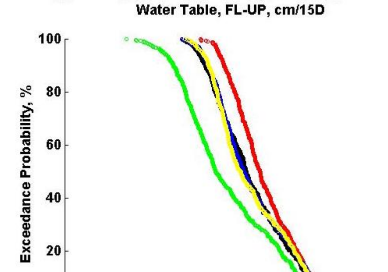

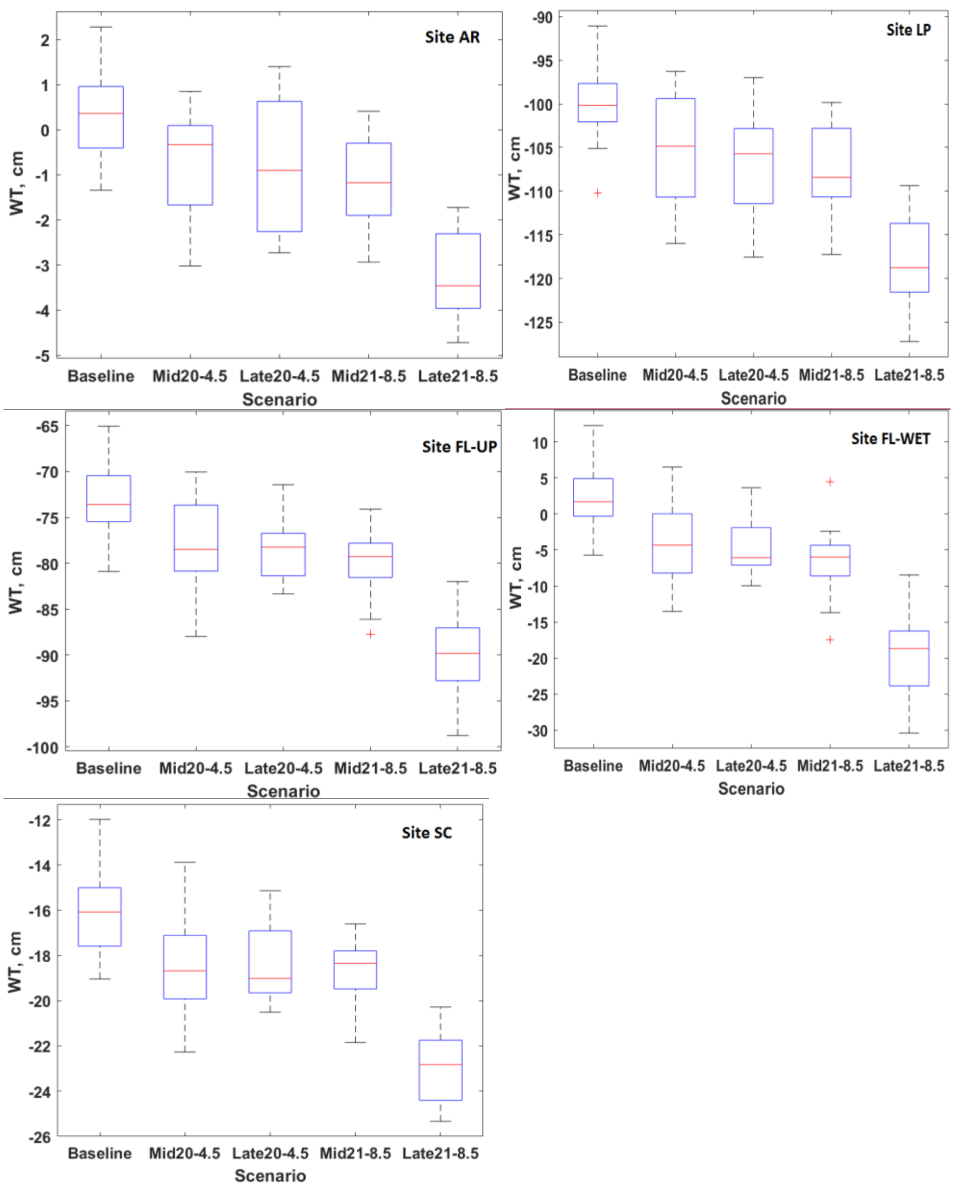

Fig. 5 Mean predicted annual water table of 20 GCMs in five wetlands in the southeastern United States (unit: cm).

Note: Baseline: 1980–1999, historical run of GCMs;

Mid 20-4.5: 2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;

Mid 21-8.5: 2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;

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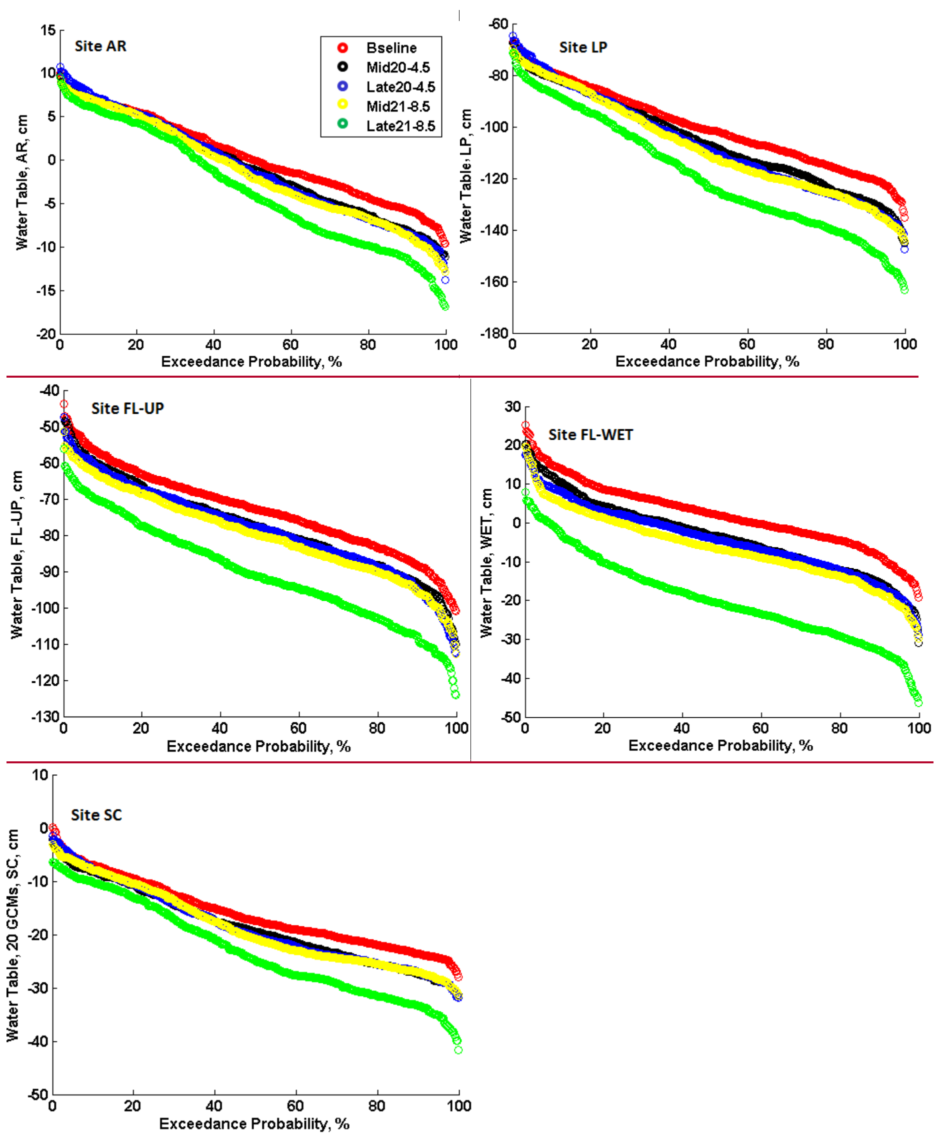

Fig. 6 Exceedance probability of the mean predicted water table in the growing season of 20 GCMs in five wetlands in the southeastern United States (unit: cm).

Note: Baseline: 1980–1999, historical run of GCMs;

Mid 20-4.5: 2040–2059, RCP 4.5; Late 20-4.5:2080–2099, RCP 4.5;

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Mid 21-8.5: 2040–2059, RCP 8.5, Late 21-8.5:2080–2099, RCP 8.5;

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(4) Author's changes in supplementary materials

Supplementary Materials

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Table list:

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Table S1 Summary of the 20 CMIP5 GCMs used in this study from the downscaled MACA dataset.

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Table S2 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in wetland AR.

Table S3 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in wetland LP.

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Table S4 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in wetland SC.

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Table S5 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in FL–UP.

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Table S6 Annual changes averages of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in FL–WET.

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Figure list:

Fig. S1 Mean annual air temperature of 20 GCMs (unit: Deg C).

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Fig. S2 Mean annual PET of 20 GCMs (unit: mm).

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Fig. S3 Total annual precipitation of 20 GCMs (unit: mm).

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Tables and Figures

Table S1 Summary of the 20 CMIP5 GCMs used in this study from the downscaled MACA dataset.

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No.	Model Name	Country	Model Institution	Atmosphere Resolution (Lon x Lat)
1	bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration	2.8 deg x 2.8 deg
2	bcc-csm1-1-m	China	Beijing Climate Center, China Meteorological Administration	1.12 deg x 1.12 deg
3	BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University, China	2.8 deg x 2.8 deg
4	CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis	2.8 deg x 2.8 deg
5	CCSM4	USA	National Center of Atmospheric Research, USA	1.25 deg x 0.94 deg
6	CNRM-CM5	France	National Centre of Meteorological Research, France	1.4 deg x 1.4 deg
7	CSIRO-Mk3-6-0	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	1.8 deg x 1.8 deg
8	GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
9	GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
10	HadGEM2-ES	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg
11	HadGEM2-CC	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg
12	inmcm4	Russia	Institute for Numerical Mathematics, Russia	2.0 deg x 1.5 deg
13	IPSL-CM5A-LR	France	Institut Pierre Simon Laplace, France	3.75 deg x 1.8 deg
14	IPSL-CM5A-MR	France	Institut Pierre Simon Laplace, France	2.5 deg x 1.25 deg
15	IPSL-CM5B-LR	France	Institut Pierre Simon Laplace, France	2.75 deg x 1.8 deg
16	MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies,and Japan Agency for Marine-Earth Science and Technology	1.4 deg x 1.4 deg
17	MIROC-ESM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
18	MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
19	MRI-CGCM3	Japan	Meteorological Research Institute, Japan	1.1 deg x 1.1 deg
20	NorESM1-M	Norway	Norwegian Climate Center, Norway	2.5 deg x 1.9 deg

Table S2 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in site AR.

Scenario	WT mean (cm/365d)	WT min (cm/365d)	P-PET (mm/365d)	P (mm/365d)	PET (mm/365d)	AT (Deg C/365d)
B	0	-1	290	1266	977	16.5
F1	-1	-3	233	1295	1062	18.1
F2	-1	-3	215	1322	1107	18.9
F3	-2	-3	199	1298	1100	18.8
F4	-4	-5	106	1303	1198	20.4
ΔF1B	-1	-2	-57	29	85	1.6
ΔF2B	-1	-2	-75	56	130	2.4
ΔF3B	-2	-2	-91	32	123	2.3
ΔF4B	-4	-4	-184	37	221	3.9

Note: B:1980-1999, historical baseline; F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4; Values of ΔFnB (n=1, 2, 3, 4) indicate the values of scenario Fn minus values of baseline scenario.

Table S2 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in site LP.

Scenario	WT mean (cm/365d)	WT min (cm/365d)	P-PET (mm/365d)	P (mm/365d)	PET (mm/365d)	AT (Deg C/365d)
B	-100	-110	313	1275	963	16.1
F1	-106	-116	263	1318	1055	17.9
F2	-107	-118	241	1343	1103	18.7
F3	-108	-118	231	1325	1093	18.5
F4	-119	-127	138	1338	120	20.4
ΔF1B	-6	-6	-50	43	92	1.8
ΔF2B	-7	-8	-72	68	140	2.6
ΔF3B	-8	-8	-82	50	130	2.4
ΔF4B	-19	-17	-175	63	238	4.3

Note: B:1980-1999, historical baseline; F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4; Values of ΔFnB (n=1, 2, 3, 4) indicate the values of scenario Fn minus values of baseline scenario.

Table S3 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in site SC.

Scenario	WT mean (cm/365d)	WT min (cm/365d)	P-PET (mm/365d)	P (mm/365d)	PET (mm/365d)	AT (Deg C/365d)
B	-16	-19	142	1192	1050	18.1
F1	-18	-22	67	1217	1150	19.8
F2	-18	-21	60	1262	1202	20.6
F3	-19	-22	49	1241	1192	20.5
F4	-23	-25	-65	1252	1316	22.4
B	-16	-19	142	1192	1050	18.1
ΔF2B	-2	-2	-82	70	152	2.5
ΔF3B	-3	-3	-93	49	142	2.5
ΔF4B	-7	-6	-207	60	266	4.3

Note: B:1980-1999, historical baseline; F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4; Values of ΔFnB (n=1, 2, 3, 4) indicate the values of scenario Fn minus values of baseline scenario.

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Table S4 Annual changes of climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in FL–UP.

Scenario	WT mean (cm/365d)	WT min (cm/365d)	P-PET (mm/365d)	P (mm/365d)	PET (mm/365d)	AT (Deg C/365d)
B	-73	-81	165	1318	1153	20.6
F1	-78	-88	83	1333	1250	22.2
F2	-78	-83	74	1376	1302	22.9
F3	-80	-88	46	1338	1292	22.8
F4	-90	-99	-124	1297	1420	24.6
ΔF1B	-5	-7	-82	15	97	1.6
ΔF2B	-5	-2	-91	58	149	2.3
ΔF3B	-7	-7	-119	20	139	2.2
ΔF4B	-17	-18	-289	-21	267	4.0

Note: B:1980-1999, historical baseline; F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4; Values of ΔFnB (n=1, 2, 3, 4) indicate the values of scenario Fn minus values of baseline scenario.

Table S5 Annual changes in averages of future climate variables of 20 GCMs for WT, P-PET, P, PET, and AT in FL–WET.

Scenario	WT mean (cm/365d)	WT min (cm/365d)	P-PET (mm/365d)	P (mm/365d)	PET (mm/365d)	AT (Deg C/365d)
B	2	-6	165	1318	1153	20.6
F1	-4	-14	83	1333	1250	22.2
F2	-5	-10	74	1376	1302	22.9
F3	-7	-17	46	1338	1292	22.8
F4	-20	-30	-124	1297	1420	24.6
ΔF1B	-6	-8	-82	15	97	1.6
ΔF2B	-7	-4	-91	58	149	2.3
ΔF3B	-9	-11	-119	20	139	2.2
ΔF4B	-22	-24	-289	-21	267	4.0

Note: B:1980-1999, historical baseline; F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4; Values of ΔFnB (n=1, 2, 3, 4) indicate the values of scenario Fn minus values of baseline scenario.

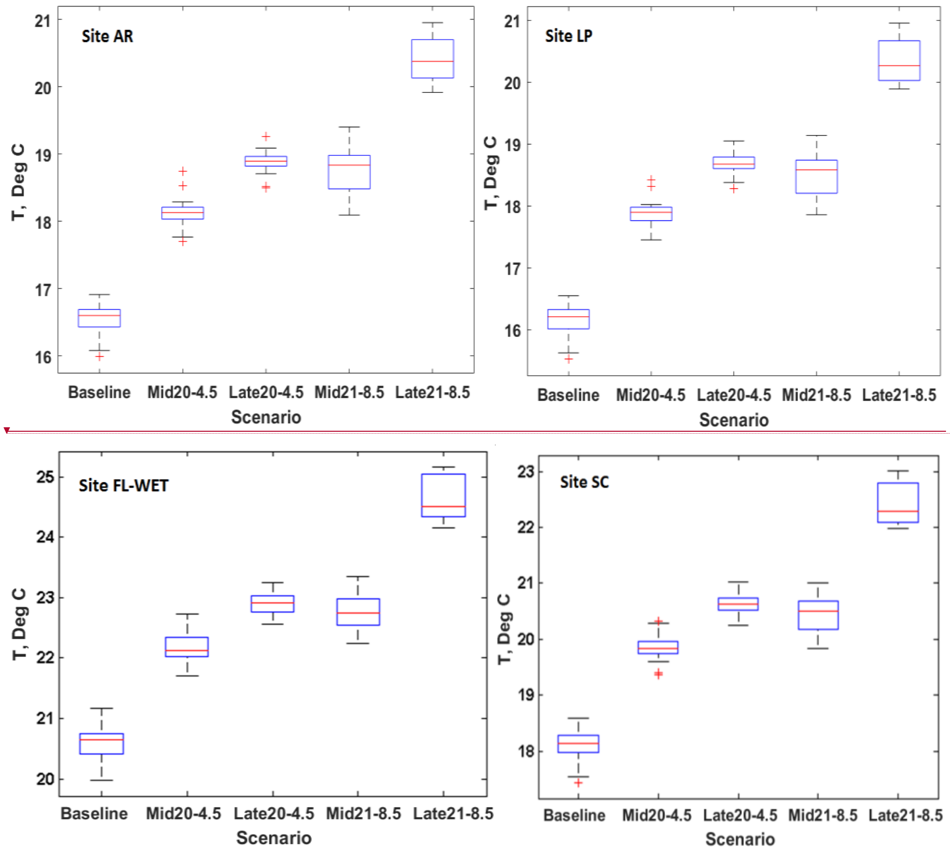

Fig. S1 Mean annual air temperature of 20 GCMs (unit: Deg C).

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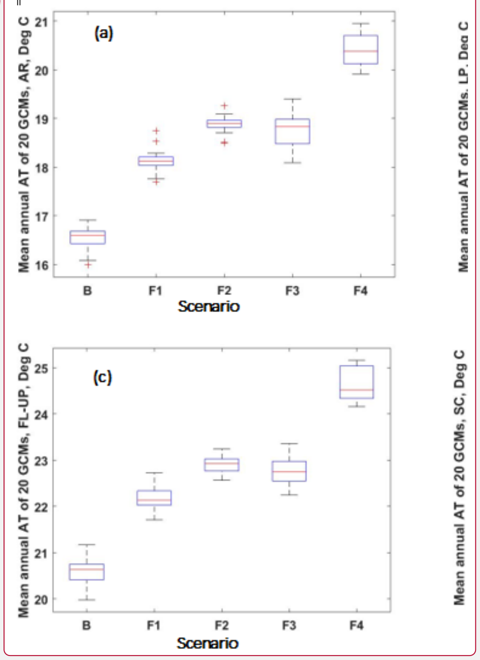

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F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; ¶
F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4;¶
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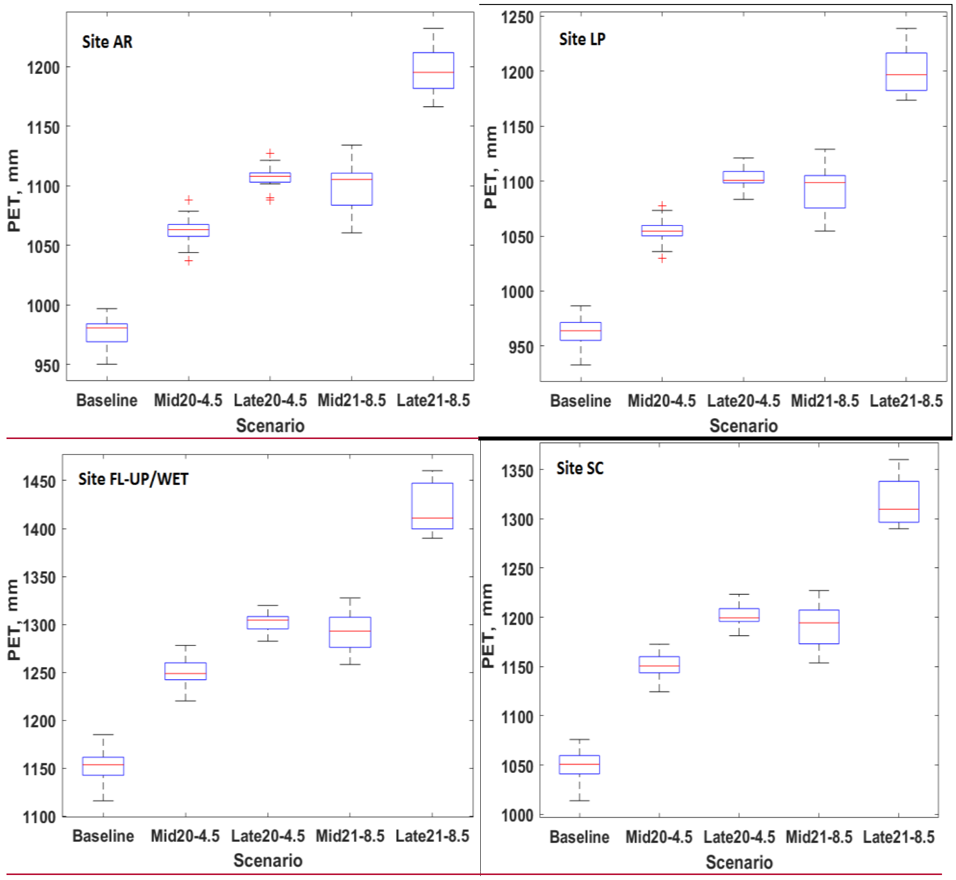

Fig. S2 Mean annual PET of 20 GCMs (unit: mm).

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F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; ¶
F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4;¶
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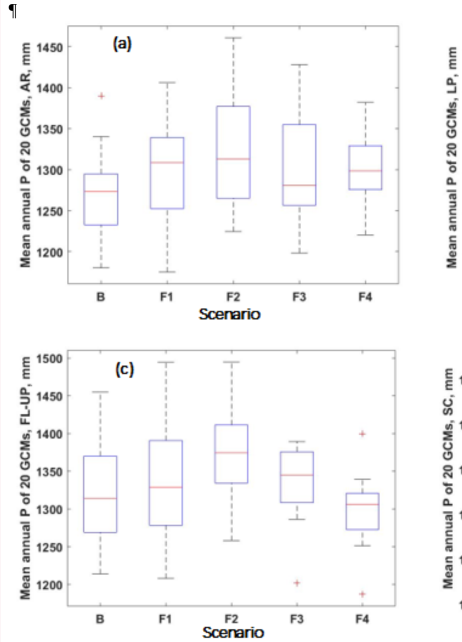

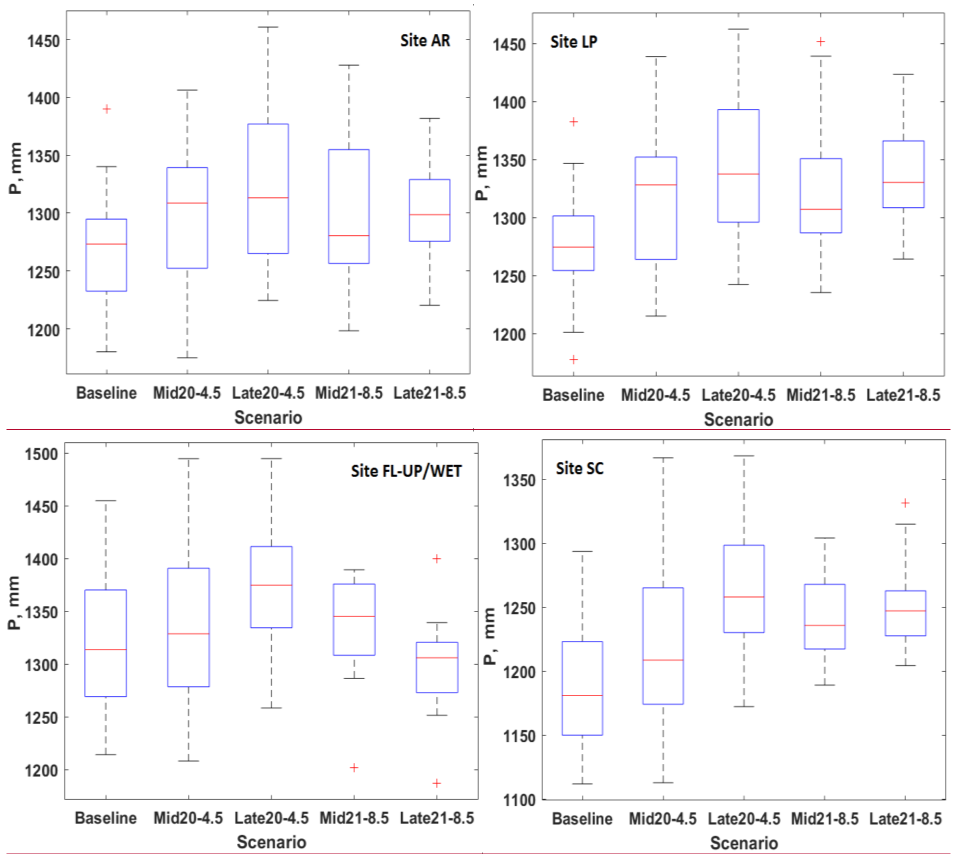

Fig. S3 Total annual precipitation of 20 GCMs (unit: mm).

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F1:2040-2059, RCP 4.5, future scenario 1; F2:2080-2099, RCP 4.5, future scenario 2; ¶
F3:2040-2059, RCP 8.5, future scenario 3; F4:2080-2099, RCP 8.5, future scenario 4;¶